Extreme Weather and Ratings on Corporate Climate Mitigation Policies [*]

Dong Chen[1]

Abstract

Using county-level data on severe meteorological events in the United States, I show that, controlling for county fixed effects, the annual number of extreme weather events (EWEs) sustained at a county significantly improves the subsequent rating of the climate mitigation policies of a firm headquartered in that county. I also find that more recent EWEs have a more pronounced impact on climate ratings than more distant ones. The results show that managerial experiential processing of weather information is important to determine corporate climate actions.

This draft: October 29, 2019
First draft: January 9, 2018

Keywords: climate change; corporate environmental responsibility; corporate climate policy; climate rating; experiential processing

[1] University of Baltimore, 1420 N Charles St, Baltimore, MD 21201. dchen@ubalt.edu, (410)837-4919, (410)837-5722 (fax)

1. Introduction

There is probably no environmental issue that has more divergence between scientific support and public reception than anthropogenic climate change (ACC) or global warming (GW).[2] Despite the critical importance and overwhelming evidence in support of ACC (Cook et al., 2013), it fails to generate consistent public support in the U.S., resulting in a failure to enact federal legislations to limit greenhouse gas (GHG) emissions (Dunlap and McCright, 2008; Leiserowitz et al., 2017; Wallach, 2012). This means that individuals and firms are mostly on their own to make decisions that can bear serious consequences on future climate (IPCC, 2012; Melillo et al., 2014; Stern, 2007). Understanding the determinants of these decisions is therefore of utmost importance.

To a certain extent, a faith in science may be indispensable for most people to accept ACC, because an accurate understanding of this topic is possible only when a person can process sophisticated statistical information embedded in the systematic (gradual) shift of average weather conditions over a long period of time (Weber, 2010). But most people lack such a capability. Instead, they depend more on affective experiencing of daily weather to form beliefs about climate change (Howe et al., 2013; Marx et al., 2007; Zaval et al., 2014). This is one of the fundamental reasons for the disconnect between scientific evidence and public understanding of ACC. Because GW is expected to result in more frequent and/or powerful incidences of many types of extreme weather events (EWEs) (IPCC, 2012; Melillo et al., 2014), experiencing these weather events may increase the salience of climate risk and enhance or change a person's belief in ACC, and alter his/her behavior. Again, it needs to be stressed that this "experiential learning" of ACC is not necessarily scientific, because the attribution of a single incidence of EWE to ACC or natural

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[2] I use *global warming* and *climate change* interchangeably in this paper, though strictly speaking *climate change* is a broader concept than *global warming*. While climate change can encompass any change in the state of the climate that can persist for an extended period (IPCC, 2012), global warming refers to a specific climate change that causes an increase in the average temperature of the atmosphere.

variability is a non-trivial task (National Academies of Science, 2016). Nonetheless, a growing line of literature has shown that individuals are more likely to express sympathy for ACC after experiencing EWEs (Demski et al., 2017; Myers et al., 2013; Rudman et al., 2013; Spence et al., 2011; Taylor et al., 2014). Given that corporate managers are humans, it is reasonable to hypothesize that they are subject to similar processes as characterized by a typical individual's perception of ACC, which may result in corporate actions to mitigate its impact. Indeed, a number of studies in finance have shown that direct exposure to natural disasters by corporate managers will increase the salience of the disaster risk and alter the risk-taking corporate policies (e.g., Bernile et al., 2017; Dessaint and Matray, 2017). In this paper, I extend these studies to examine the impact of EWEs on managerial experiential learning of ACC and the resulting corporate climate mitigating policies.

To that effect I analyze whether the annual number of EWEs sustained at the headquarter county of a firm has any effect on its willingness to take climate-friendly actions. I use a third party's rating to capture the degree of friendliness of a firm's climate policy. I measure EWEs at a firm's headquarter because headquarters are the primary locales where managers of the firm reside (Pirinsky and Wang, 2010). Therefore, it is more likely that they have personally experienced these weather events. However, lacking data to directly indicate this, I cannot rule out the possibility that other employees of the firm residing in the same area or community residents/customers, after witnessing EWEs or suffering great losses from them, push managers to engage more in climate actions. Even though these explanations are plausible, they do not change the basic intuition that experiential learning of climate change, be that by managers themselves or local stakeholders of a firm, matters for corporate climate policies.

The focus on the *number of*, rather than the *economic damages* caused by EWEs is due mostly to data limitations.[3] A legitimate concern is that some of the EWEs may not be severe enough to induce climate actions. This concern is alleviated by the fact that the EWE database I employ, the Storm Database from the National Oceanic and Atmospheric Administration (NOAA), records only exceptional meteorological events with the "intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce" (NWS, 2016).[4] Specifically, I include heat wave, drought, wildfire, and flood in my EWE variable definition, because these events are predicted to increase with ACC with relatively low uncertainty (Melillo et al., 2014).[5] Despite the apparent advantage of using economic damages based commonly on insurance data, there are practical difficulties such as its coarser geographic resolution and the risk to jeopardize the exogeneity of the EWE variable.[6]

My major results are summarized below. Using a sample of the largest public companies in the U.S. from 1997 to 2009, I document a positive and significant impact of EWEs sustained at the headquarter county of a firm and its *subsequent* climate rating. Importantly, I show that the significance of the result rests critically on controlling for county fixed effects (FEs), which suggests that in experiential learning of ACC through EWEs, managers have factored the possibility that climate change implies a *change in*, rather than the different regional *levels* of

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[3] Though I lack the insurance data for the economic damages of all the EWEs, I use the NOAA Billion-Dollar Disasters Database with estimated losses by the "mega-disasters" causing at least $1 billion inflation-adjusted damages for robustness checks and obtain similar results. The results are presented in Table 5.

[4] Though the Storm Database includes the damage data for EWEs, a large number of them are missing. The available data suffer from significant quality issues since NOAA is not required and may not be qualified to report such data. Therefore, I do not use the damage data from the Storm Database in the analysis.

[5] The change in the frequency of other EWEs and their human influences are more uncertain, including hurricanes, tornadoes, hail, thunderstorms, and winter storms. In the Internet Supplementary I show the robustness of the results by including these and other weather events that may also increase with ACC.

[6] Most of the insurance data are at the state level. Since the purchase of insurance is voluntary, the data often suffers from a selection bias. Besides, it is challenging to adjust for factors such as demand surge and climate adaptation to accurately estimate the economic damages caused by a EWE (e.g., Pielke Jr. et al., 2008; Simmons et al., 2013; Smith and Katz, 2013). These adjustments could even make the damage variable to be endogenous (Miao and Popp, 2014), hence jeopardizing the study of a causal impact of EWEs on climate ratings.

extreme weather into consideration. As further evidence in support of experiential processing, I document results which are consistent with a managerial "recency heuristic" where more recent EWEs have a more pronounced impact on climate ratings than more distant ones (Marx et al., 2007).

To the author's best knowledge, this is the first study that analyzes how presumably managerial experiencing of EWEs matters for corporate climate actions. It separates from the environmental psychology literature on individuals (survey takers) and their *stated beliefs* in ACC by focusing on firms and *climate actions* as captured by third-party ratings. The distinction between belief and action is important because evidence suggests that stated concern for ACC does not necessarily translate into concrete actions (GS Sustain, 2009). Unlike the cross-sectional nature of the studies in environmental psychology based on surveys, I employ a panel data and document evidence that seems to be more consistent with what climate change implies - the *change*, rather than the regional differences in EWEs matters more for climate ratings.

I also add to the small but growing literature which examines the impact of weather on asset pricing and corporate finance. Among these, Hirshleifer and Shumway (2003) and Goetzmann et al. (2015) document that weather affects investors' mood and asset prices. Bernile et al. (2017) and Dessaint and Matray (2017) show that exposure to natural hazards influences managerial propensity for risk-taking. I advance this line of research by showing that experiencing of adverse weather may also alter managerial perception of ACC and climate actions, and hence document another channel through which weather can affect corporate policies.

The balance of the paper is organized as follows. Section 2 develops the hypotheses to be tested later. Section 3 describes the data, variables, methodologies, and summary statistics. Section 4 presents the empirical results. Section 5 conducts robustness checks. Finally, Section 6 concludes.

2. Hypothesis Development

The consensus in the scientific community that GW is mainly caused by the burning of fossil fuels by human beings is based on more than 100 years' data and observations (National Research Council, 2010). Fully understanding these observations requires sophisticated modeling skills and statistical capabilities. Because most lay people lack these abilities, absent of an ACC-related curriculum in formal educational systems, their main exposure to the knowledge of GW is through media and films, which is subject to the issue of trust (Weber, 2010). The perception of ACC is further complicated by social, institutional, cultural and partisan factors (Hulme, 2009). Thus, analytical processing of scientific information alone is unlikely for most people to accurately understand the abstract issue of ACC.

In contrast to analytical processing which requires conscious and costly cognitive efforts, experiential processing works automatically (Marx et al., 2007). Strong feelings such as joy, fear, and horror are often evoked during this process, making the experiences memorable and dominant in information processing (Loewenstein et al., 2001). Positive feelings are often associated with approaching behavior and negative feelings may elicit rejection. Evidence suggests that decision makings of not only the general public, but also professional managers of large firms with multi-billion-dollar assets are influenced by experience-induced affect (e.g., Bernile et al., 2017; Dessaint and Matray, 2017; Goetzmann et al., 2015; Hirshleifer and Shumway, 2003).

The above discussions suggest that although climate change is not easily and accurately detected by personal experiences because it refers to a long run gradual shift of average weather conditions, most people still mainly rely on their experiences to perceive it (Weber, 2010). It is because of this fact that daily weather becomes an important mediator for most people to understand GW. Since experiencing-associated affect is expected to be stronger the more intense

the experiences are, EWEs have the potential to strengthen or change the beliefs of managers in ACC and motivate them to take climate-friendly actions (Leiserowitz, 2006).

There are at least two assumptions for the above prediction to hold. First, there needs to be a connection between EWEs and ACC. Many of the extant climate models provide such a connection - many types of EWEs are expected to become more frequent and/or powerful with GW, especially heat waves, droughts, wildfires, and floods (IPCC, 2012; Melillo et al., 2014). However, regional differences exist for many of these weather events. For example, California has historically suffered significantly more from droughts and wildfires than many other states, while southern areas are more likely to experience heat waves. Therefore, the impact of the frequency of EWEs on climate actions is expected to be dependent on controlling for the regional differences in the exposure to EWEs. A common way to do this is to detrend a variable based on its long-run historical regional average, typically over more than 10 years (e.g., Egan and Mullin, 2012; Konisky et al., 2016). In my context, however, this methodology is infeasible because the Storm Database did not start the comprehensive coverage of the EWEs until 1996, and my sample starts at 1997. Therefore, I choose to include county FEs in the regression models.

A second assumption for the validity of the prediction that experiencing EWEs will motivate managers to be more cognizant of ACC and take more climate actions is that managers need to be aware of the connection between the frequency of EWEs and ACC. Absent of this, personal experiences may not result in increased concern for ACC (Whitmarsh, 2008). Since professional managers are typically more knowledgeable than the general public and the media coverage of climate change has been increasing over time (Boykoff, 2009), such a managerial awareness is expected. Therefore, the two assumptions as discussed above coupled with the consideration of the regional differences in the exposure to EWEs leads to my first hypothesis:

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H1: Controlling for the regional differences in the incidences of EWEs, the frequency of EWEs will be positively associated with climate ratings.

Since experiential processing gives significant weight to recent observations (Marx et al., 2007), more recent EWEs are expected to have a stronger impact on climate ratings than more distant ones. This leads to my second hypothesis:

H2 (Recency Hypothesis): More recent EWEs have a stronger impact on climate ratings than more distant ones.

3. Data, Methodology, and Summary Statistics

3.1. Data and Variables

I describe the data and major variables of interest in this section. Appendix A provides the detailed definitions of all the variables.

The sample used in the empirical analysis is an intersection of several databases. The corporate social responsibility (CSR) data are from the KLD STATS database, which is derived from the proprietary research by KLD Research & Analytics on the ESG (environmental, social, and governance) policies of the largest public firms in the U.S. The accuracy of the KLD data is corroborated by several studies (e.g., Chatterji et al., 2009; Sharfman, 1996). Its coverage has expanded over time, starting at 1991 with around 650 firms to about 3,100 firms since 2003. My KLD data ends at 2012. The data cover more than 60 ESG indicators in seven categories: environment, community, human rights, employee relations, diversity, customers, and governance. The ratings are reported at the end of a calendar year.

The KLD ratings are a binary variable indicating either a strength or concern. According to the data guide, the strength/concern is assigned a value of 1 if a company meets the (proprietary) criteria as established for a rating, and 0 otherwise. There are two climate change related policy

ratings in the database, Climate strength (env_str_d) and Climate concern (env_con_f). As discussed in the Internet Supplementary, I focus on the years before 2009 because the definition of Climate strength was changed significantly following the acquisition of KLD by MSCI in 2010. As suggested in the data guide, an issue with the KLD database prior to 2009 is that a rating of zero may either mean that a firm did not meet the criteria established for a rating, or that the rating was not applicable to the firm's industry.[7] The latter possibility would introduce noises into the empirical analysis. This issue applies to both climate strength and concern ratings. Between them, the concern rating is relevant for an even smaller set of industries, as suggested by its definition in Appendix A. Specifically, the concern rating is only applicable to petroleum, utility, and transportation industries. In contrast, Climate strength may be applicable to a wider range of industries. To see this, I list in Table 1 the average values of Climate strength and Climate concern by industries as classified by three-digit SIC codes. I consider the possibility that Climate strength may be irrelevant for some industries by excluding industries with zero strength ratings throughout the sample period. Some industries have very sparse incidences of strength ratings, which might be due to data collection error by KLD. To consider this, I also exclude industries whose average Climate strength value is less than 0.01, and industries whose number of firm-years is fewer than five because the small sample makes it difficult to determine whether the strength rating is relevant for these industries. These screenings excluded about 75%/60% of the industries/firms from the sample. In Section 5 I show the robustness of the results by including all the industries/firms in the sample.

Insert Table 1 about here

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[7] The 2011 user guide stated that the rating methodologies have changed significantly since 2010, with one of the changes being the "introduction of industry specific ESG ratings templates for each of the seven ESG ratings categories". Starting from 2010, MSCI will assign a rating of "NR (Not Rated)" if a specific rating is not relevant for an industry. This suggests that prior to 2010 KLD did not consider the industry applicability of its ratings.

The statistics in Table 1 confirm that while Climate concern may be relevant for only a small set of industries, the industry applicability of Climate strength is much wider. This suggests that firms have more leeway to earn a climate strength rating than dropping a concern rating. While the latter may require a firm to exit a polluting industry altogether (which may well violate the fiduciary responsibilities of its managers), the former only asks it to engage more in renewable energy generation and/or carbon reduction in relatively non-core operations, as suggested by the definition of Climate strength in Appendix A. A specific example may help illustrate this point. Exxon Mobil, a petroleum refining firm (three-digit SIC code=291) that has incurred multiple ACC-related litigation and had a climate concern rating throughout the sample period, nonetheless received a strength rating since 2007. Though the proprietary nature of the KLD ratings prevents a full understanding of this result, my search of the proxy statements of this company and the internet suggests some possible reasons:[8]

1. The company has improved the energy efficiency of its refineries, which resulted in a reduction of "GHG emissions by about 5 million metric tons in 2007, equivalent to removing about one million cars from the U.S. roads". As noted by the company, energy efficiency and flaring are two major drivers of GHG emissions.

2. Its Baton Rouge Refinery was presented EnergyStar Award by the EPA partly in recognition of its effort to reduce flaring by 69% compared to 2004.

3. It was investing about $3 billion in Nigeria to effectively eliminate gas flaring by 2008.

4. It sold or closed some coal mines at around 2007.

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[8] The 2008 proxy statement that mentioned some initiatives the company took in 2007 to reduce GHG emissions was available at: https://www.sec.gov/Archives/edgar/data/34088/000119312508078618/ddef14a.htm. The news article that mentioned that the company sold or closed some coal mines was available at: https://www.sj-r.com/article/20090127/NEWS/301279892.

The above notes suggest, paradoxically, that more polluting firms actually have more opportunities to engage in actions to earn a climate strength rating, an observation that complements with earlier findings that these firms engage in CSR initiatives to reduce the potential liabilities of corporate social *irresponsibility* (Jo and Na, 2012; Kotchen and Moon, 2012). Indeed, in my sample the correlation between the climate strength and concern ratings is 0.11, and highly significant.

Because the primary purpose of this study is to examine the potential impact of a direct exposure to EWEs by managers on corporate climate actions, and because managers have more leeway to change the climate strength rating than concern rating as discussed above, I use Climate strength as my primary dependent variable in the empirical examinations. Without causing any confusions, I term Climate strength as Climate rating subsequently.

I create two additional variables from the KLD data to consider the fact that CSR investments are typically clustered: one with all the ratings in corporate environmental responsibility (CER) category other than Climate rating (Net CER), and the other with all the CSR ratings in categories other than environment (Net CSR).[9] Because the availability of the KLD variables changes over time, the extant studies have employed different methods to define Net CER/CSR (e.g., Benson and Davidson III, 2010; Cai et al., 2011; Goss and Roberts, 2011; Harjoto et al., 2017; Jo and Harjoto, 2012). In my primary specification I follow Benson and Davidson III (2010) to define these two variables, but as I show in the Internet Supplementary, the results are robust to other definitions.

The data on EWEs are from the NOAA Storm Events Database, which records severe meteorological events such as hurricane, lightning, cold/wind chill, flood, etc. at the county level

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[9] The results are robust to including or excluding the governance category in Net CSR.

in the U.S. starting from 1996. The Internet Supplementary lists the weather events that are covered by this database. The database is excellent at recording short-duration events such as storms but deficient in the coverage of long-lasting events such as droughts. Therefore, I examine the robustness of the results by excluding drought from the definition of the EWE variable (EWE) in Section 5.

The specific weather events used in the definition of EWE are listed in Appendix B, which also groups the events into four categories: heat event, drought, wildfire, and flood. In the Internet Supplementary, I show the robustness of the results using an alternative definition of EWE with a more comprehensive list of weather events. To facilitate interpretation, I standardize EWE to have a mean of 0 and a standard deviation of 1.

It is worthwhile to comment here on the advantages and disadvantages of using actual weather vs. surveys to proxy for the experiences of individuals, as is commonly done in the literature on environmental psychology. As mentioned earlier, using the actual data has the disadvantage of not being able to directly measure managerial exposure to EWEs, though the fine level of geographic resolution as employed in the study makes this likely. However, using survey data also has many disadvantages. In particular, survey takers' stated "experiences" may be influenced by their pre-existing beliefs for ACC, which complicates the interpretation of a relationship between experiences and beliefs (Demski et al., 2017; Egan and Mullin, 2012). In my context, a survey on managers' EWE experiences may still be subject to the critique of reverse causality, that managers who have decided to adopt a climate-friendly policy will tend to report that they have experienced EWEs to justify their actions. In contrast, the exogeneity of actual weather events makes the interpretation of a relationship between EWEs and climate ratings unambiguous.

The financial data are from COMPUSTAT, including the data on headquarter counties. One drawback of this data is that it lists only the headquarters at the date when the data is extracted, which are years 2006 and 2011 in my case. To fill in the missing data, I assume that the headquarters for the years on or before/after 2006 are the same as those of 2006/2011. Empirically few firms change headquarters (Pirinsky and Wang, 2006). For robustness I manually collected the historical headquarter county data for the S&P 500 firms at 2006 over my sample period (between 1997 and 2009), and show that the results are similar in Section 5.

Since climate policies are part of CSR, I follow the literature on the determinants of CSR for the control variables in the regressions (Aggarwal and Dow, 2012; Baron et al., 2011; Di Giuli and Kostovetsky, 2014; Jiraporn et al., 2014), including firm size, sales growth, return on assets (ROA), leverage, dividend payout, capital expenditure, R&D and advertising expenditures, and cash balance. All the control variables are winsorized at the 1st and 99th percentiles to consider outliers.

Even though climate ratings are reported at the end of a calendar year, the relevant polices may be determined earlier in the year. Therefore, I lag EWE by one year in the analysis to rule out the possibility that some EWEs incurred in the year may be after the date when the climate policy is determined. Because the coverage of the Storm Database began in 1996, this suggests that the primary variable of interest, EWE, starts at 1997. To alleviate the concern for endogeneity, all the control variables are also lagged by one year. As reported in the Internet Supplementary, the results are qualitatively similar if using contemporaneous levels of EWE and the control variables. After merging various sources of data and deleting singleton observations, the final sample covers the period between 1997 and 2009 with 7,706 firm-year observations, 1,526 firms, and 334 headquarter counties.

3.2. Methodology

Since the dependent variable, Climate rating, is a dummy variable, it is most suitable to employ a probit/logit model for the empirical analysis. However, nonlinear models suffer from the "incidental parameter" problem with the inclusion of a large number of FEs (Neyman and Scott, 1948). As mentioned earlier, controlling for these FEs is critical for the analysis. Therefore, I employ linear models as the primary specification, but use a probit model to examine the robustness of the results in Section 5. My primary empirical specification is as follows:

$$Climate\ rating_{i,j,k,t} = \beta_0 + \beta_1 * EWE_{j,t-1} + \overline{Control\ Variables_{i,j,k,t-1}}'\overline{\beta_2}$$

$$+\alpha_j + \mu_k * \tau_t + \varepsilon_{i,j,k,t} \tag{1}$$

In the above equation, $Climate\ rating_{i,j,k,t}$ is the climate rating of firm i headquartered at county j and operated in industry k in year t. $EWE_{j,t-1}$ is the number of EWEs incurred at county j in year t-1. α_j, μ_k, and τ_t are the county, industry, and year FE, respectively. In the Internet Supplementary, I show that the results are similar if also including the firm FEs. The interaction of industry and year FEs is to consider the industry-specific shocks at a given year such as the adjustment of rating criteria for some industries in a given year (though not as dramatic as the adjustment in 2010). I classify industries based on three-digit SIC code. I show in the Internet Supplementary that the results are robust to alternative industry classifications. My primary variable of interest is β_1. Standard errors are adjusted for heteroscedasticity and clustered at the both the firm (for autocorrelation) and county-year levels (for the possibility that climate policies of neighboring firms in a given year may be correlated).

3.3. Summary Statistics

Table 2 reports the summary statistics of the major variables. As can be seen, the incidence of Climate rating is sparse with a mean of 0.09 and a median of 0. The average annual number of

EWEs in the sample is 4.95, with a standard deviation of 6.62. The statistics are similar using a county-level sample which keeps only one observation for all the firms headquartered in the same county in a year, with a mean of 4.53 and a standard deviation of 6.63. This county-level sample is free of the bias caused by the uneven distribution of headquarters in different counties. The statistics also show that out of the standard deviation of 6.63, 5.59/2.87 comes from cross-sectional/within-county variation. The within-county variation is critical for the implementation of FE models (Zhou, 2001).

<div align="center">Insert Table 2 about here</div>

Table 2 also lists the summary statistics of the four categories of EWEs. The statistics show that the most common EWEs are heat events and floods. In contrast, droughts and wildfires are less common. The summary statistics for the control variables largely accord with prior studies (e.g., Di Giuli and Kostovetsky, 2014; Jiraporn et al., 2014).

4. Empirical Results

In this section I examine the two hypotheses as developed in Section 2. I use two methods to highlight the importance of controlling for county FEs, t-tests based on matched pairs and regressions. I conduct two types of matching. First, I match firms suffering more from EWEs with those suffering less (stratified by sample median) by industry and firm size. This matching generates 2,490 pairs. The second matching is similar except that the EWEs are *county-demeaned*. This results in 2,116 matched pairs. The t-test results for the differences between the raw/county-demeaned climate ratings of the matched pairs are presented in Panel A of Table 3.

<div align="center">Insert Table 3 about here</div>

The results show that while the difference between climate ratings is insignificant for the sample based mainly on cross-sectional variations of EWEs, it is highly significant for the sample based

on within-county variations. Therefore, netting out the regional differences in the exposure to EWEs is important in the relationship between EWEs and climate ratings.

In Panel B I run regressions to formally test H1 on the relationship between EWEs and climate ratings. I start with an OLS regression with only industry and year FEs in Model 1. The coefficient on EWE is not significant, which is consistent with the *t*-test results based on cross-sectional variations of EWEs. However, In Model 2 when I add the county FEs to net out the regional differences in the incidences of EWEs, EWE becomes positive and highly significant at the 1% level. This result is consistent with the prediction of H1. Instead of controlling for the individual industry and year FEs as in the first two models, I include their interactions in Model 3. The coefficient on EWE is smaller but remains significant. In Model 4 I add the control variables to be consistent with Equation (1). EWE continues to be highly significant, though the magnitude of the coefficient further decreases. The results also show that the two CSR variables, Net CER and Net CSR, are positive and significant. This suggests that firms often engage in multiple CSR activities at the same time. It is also notable that firm size is positively associated with climate rating, which suggests that larger firms are more likely to engage in climate actions. This result and the signs on many other control variables accord with prior literature, except for ROA (e.g., Aggarwal and Dow, 2012; Di Giuli and Kostovetsky, 2014; Jiraporn et al., 2014). Though many studies document a positive effect of ROA on CSR (e.g., Di Giuli and Kostovetsky, 2014; Jiraporn et al., 2014), I find a negative effect of ROA on Climate rating. In unreported analysis, I confirm that the effect of ROA on CSR is positive and significant, suggesting that the impacts of ROA on climate and other CSR ratings are different. I note that Aggarwal and Dow (2012) find a negative but insignificant effect of ROA on the corporate environmental policy rating.

Turning to the economic significance of the results, the coefficient on EWE in Model 4, 0.012, suggests that on average increasing the annual number of EWEs at a county by one standard deviation (2.87) results in an upgrade of the climate rating by 0.0052 (=0.012*2.87/6.62) notch, which stands for a 5.8% improvement in the rating of the average firm (with a mean climate rating of 0.09 according to Table 2). If the impact of EWE on the probability of improving climate ratings is linear, this also suggests that a one standard deviation increase in EWE increases the probability of a firm receiving a climate rating by 5.8%. This impact of EWEs on a firm's climate engagement is not trivial, especially since a firm needs to meet the threshold set by KLD to receive a rating.

In Model 5, I examine the individual effects of the four categories of EWEs to consider the possibility that the experiences of different types of EWEs may have a different impact on climate policies. Similar to EWE, I standardize each of the four category variables to have a mean of 0 and a standard deviation of 1. The results show that among the four variables, Heat event, Wildfire, and Flood are positive and the latter two are significant. In contrast, Drought is negative but not significant. The insignificant (but significant at the 16% level) effect of Heat event is a little surprising, since heat waves are probably the most prominent weather event that is associated with GW. However, it is possible that the experiences of heat waves at different geographic regions may have a different impact on climate actions. Specifically, because of colder weather in northern regions than southern regions, warming may not feel as bad for people residing in the north as in the south. To examine this possibility, I create a dummy variable indicating whether the headquarter county is in the south based on its latitude. I obtain the data on county latitudes from the 2000 and 2010 Census Gazetteer Files. The Southern county dummy equals one if the latitude of a county is at or below the sample median, and zero otherwise. I then interact this variable with Heat event in Model 6. Interestingly, the interactive term, Heat event * Southern county is positive

and significant. After netting out this term, Heat event itself is negative but not significant. This suggests that while southern firms engage more in climate actions after experiencing more heat waves, northern firms do not. Notably, Hsiang et al. (2017) show a possible wealth transfer from southern areas to northern areas as a result of ACC.

Some discussions on the results in Table 3 are warranted at this point. Though I have argued that the results may reflect the experiential learning of ACC by managers, some may argue they are simply due to the adoption of new technologies that happen to be more climate-friendly by firms after their existing equipment and properties are being destroyed by EWEs. If this is the case, one would expect a positive impact of EWE on Climate rating regardless of whether county FEs are controlled for, since it should be the damage itself rather than its region-adjusted value that matters for the replacement decision. However, the results in Table 3 are inconsistent with this prediction. Nonetheless, one could further argue that firms may have developed the disaster-defenses adaptable to local conditions, so the average EWE at a specific location also proxies for the level of the disaster-defenses for that location. Therefore, only when the impact from EWEs exceeds that level sufficiently will the affected firm adopt new technologies. However, this explanation is contradictory to a differential impact of heat waves on climate ratings, since northern firms should also have adopted more climate-friendly technologies after the more-than-usual heat events have impacted their areas.

I proceed to examine H2 in Table 4. To do this, I lag EWE by one, two, and three years, respectively, and control for these additional variables in the regressions. Because EWE is already lagged by one year, I use the symbols, EWE_{t-1}, EWE_{t-2}, EWE_{t-3}, and EWE_{t-4} to denote the primary EWE and its three lagged variables respectively. Model 1 shows that among the four variables, only the primary EWE variable (EWE_{t-1}) is significant, suggesting that the effect of EWEs on

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climate actions dissipates over time, and typically does not last for more than a year. This is consistent with managers employing a recency heuristic when experientially processing the extreme weather information. To further examine this hypothesis, I include the contemporaneous value of EWE (EWE_t) in Model 2. As mentioned the downside of using this EWE variable is the potential measurement error given that climate policies may be determined in the middle of a year. However, the results provide some further evidence consistent with H2 – among the five EWE variables, EWE_t and EWE_{t-1} have similar impacts. The EWEs that took place over a year ago do not significantly affect climate ratings. But compared to the duration of the impact of abnormal weather on individual beliefs in ACC which is typically shorter than a month (e.g., Egan and Mullin, 2012; Konisky et al., 2016), the duration of the impact of EWEs on corporate climate actions is much longer.

Insert Table 4 about here

Collectively, the results in Table 3 & 4 support the two hypotheses as developed earlier, that controlling for the regional differences in the occurrence of EWEs, the frequency of EWEs is positively associated with climate ratings and recent EWEs have a stronger impact than distant ones. These results are consistent with the notion that managerial experiential processing of weather information is significant to determine corporate climate mitigation policies.

5. Robustness Checks

I conduct several robustness checks in this section to buttress the major findings in the paper. One drawback of using the frequency of EWEs to measure managerial experiential learning of ACC is that it ignores the severity of EWEs. Though I cannot fully account for this issue due to data limitations, I partially address the issue by employing the NOAA Billion-Dollar Disasters Database to estimate the economic damages of the headquarter states caused by "mega-disasters"

incurring at least $1 billion inflation adjusted damages (Smith and Katz, 2013). I assume that the damage of a state is proportional to its GDP.[10] I then sum up the estimated damages of all the disasters affecting the state in the previous year, and "normalize" this variable using the 2009 state GDP. The normalization takes account of the different levels of wealth at stake at different points in time (e.g., Pielke Jr. et al., 2008; Simmons et al., 2013). The downside of using this disaster variable is its coarser geographic resolution hence the potential imprecision to proxy for managerial experiencing of EWEs. I examine the relationship between this economic damage variable and climate ratings in Model 1 of Table 5. To be consistent with the state-level disaster variable, I replace the county FEs with the state FEs, and cluster the standard errors at both the state-year and firm levels. The results show that Billion disaster loss is positive and significant, which is consistent with those based on the frequency of EWEs.

<center>Insert Table 5 about here</center>

As described in Section 3, one drawback of using the COMPUSTAT data is that it only has the most recent information on headquarter locations. To get around this issue, I manually collected the historical headquarter data for the S&P 500 firms at 2006 between 1997 and 2009. The sample size dropped dramatically to 2,130 firm-years. Model 2 in Table 5 reports the results. It shows that EWE continues to be positive and significant with an even larger coefficient.

In Model 3, I examine the robustness of the results using a probit model to account for the fact that the dependent variable is a dummy variable. As noted earlier, including a large number of dummy variables as in my case suggests that a probit model may not be consistent (Neyman and

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[10] I extracted the data from https://www.ncdc.noaa.gov/billions/events/US/1980-2017. I only include the disaster types "Droughts/Heat", "Flood", and "Wildfire" to be comparable to the EWE types used in the definition of the frequency variable. In a few cases where the information about states is not available, I manually check this information by matching the descriptions of the incidents with the records in the NOAA Storm Database, Federal Emergency Management Agency (FEMA) Disaster Database, and the web. The data for state GDPs are from the Bureau of Economic Analysis (BEA).

Scott, 1948). To alleviate this concern and because county FEs are the most critical for the significance of the results, I only include the county and year FEs in the model. The results show that EWE continues to be positive and highly significant, suggesting that the major findings in the paper are not sensitive to model specifications.

As mentioned, the drought data in the Storm Database is not very reliable. Therefore, in Model 4 I exclude drought from the definition of EWE. The coefficient on EWE (no drought) remains positive and highly significant.

Finally, as explained in Section 3, I excluded around 75% of the industries from the sample to consider the possibility that climate ratings may not be relevant for these industries. In Model 5 I include all the industries so the sample size increases significantly to 17,349 firm-years. EWE continues to be positive and highly significant, though the coefficient is smaller.

6. Conclusion

Although ACC is in essence an abstract scientific issue and requires analytical processing of long run average weather information to comprehend, most people rely more on their affective experiencing of daily weather to form beliefs on this issue. As such the rare but deeply impressive incidences of EWEs have the potential to "convince" some people that climate change is real and dangerous, and hence may motivate them to take mitigating actions. Prior literature in environmental psychology has focused on investigating the link between experiencing of EWEs by individuals and their concern for ACC. In the finance area, some studies have shown that a direct exposure to natural disasters can affect the risk-taking propensity of corporate managers. I extend these studies to examine how managerial experiencing of EWEs may also matter for corporate climate policies as captured by third-party ratings.

The results show that the frequency of EWEs incurred at the headquarter county of a firm is positively and significantly associated with the climate rating of the firm. Consistent with the notion that managers net out the regional expected level of EWEs during their experiential learning of ACC, I find that this result holds only when the regional differences in the exposure to EWEs are controlled for. As further evidence for experiential processing of weather information, I show that more recent EWEs have a more pronounced impact on climate ratings than more distant ones.

On the policy side, these results deliver a mixed message to the advocates of mitigating the impact of ACC in light of its urgency (IPCC, 2018). On one hand, the positive effect of EWEs on climate ratings suggests that experiential learning through EWEs may be effective to motivate some professional managers to take climate actions. On the other hand, the fact that genuine understanding of ACC requires analytical processing or a faith in science but most people including professional managers depend more on experiential processing implies significant uncertainty on the public acceptance of ACC, since the climate change in the years before its most catastrophic impact in the relatively distant future is uncertain, and can well be more pleasant as some evidence suggests (e.g, Egan and Mullin, 2016). Such "intermediate pleasantness" implies the unwillingness of many firms to take mitigating actions based on the results in the paper, yet the window of opportunity for human beings to avoid or reduce the devastating impact of ACC may well lie in those years. If vicarious learning has similar effect to learning through direct experiences, then this study offers some hope to encourage more managers to take mitigating actions by designing some education programs that permit the simulated experiencing of calamitous natural disasters that are predicted to take place with continued GW. But whether this is the case for professional managers is not clear, and is left for future studies.

Appendix A. Variable Definitions

Variable	Definition	Data Source
Climate strength/rating	Dummy variable that equals one if a firm has taken significant measures to reduce its impact on climate change and air pollution through use of renewable energy and clean fuels or through energy efficiency, or the firm has demonstrated a commitment to promoting climate-friendly policies and practices outside its own operations, and zero otherwise (env_str_d).	KLD STATS
Climate concern	Dummy variable that equals one if a firm derives substantial revenues from the sale of coal or oil and its derivative fuel products, or the company derives substantial revenues indirectly from the combustion of coal or oil and its derivative fuel products. Such companies include electric utilities, transportation companies with fleets of vehicles, auto and truck manufacturers, and other transportation equipment companies (env_con_f).	KLD STATS
Net CER	Lagged value of the total strength count of corporate environmental responsibility (CER) ratings excluding Climate rating of a firm scaled by the number of strength items excluding Climate rating in the CER category in a given year, minus the total concern count of CER ratings scaled by the number of concern items in the CER category in that year.	KLD STATS
Net CSR	Lagged value of the sum of total strength counts of community, human rights, employee relations, diversity, product quality and safety, and governance ratings of a firm scaled by their respective number of strength items in a given year, minus the sum of total concern counts of community, human rights, employee relations, diversity, product quality and safety, and governance ratings of a firm scaled by their respective number of concern items in a given year.	KLD STATS
Raw EWE	Lagged total number of severe meteorological EWEs incurred at the headquarter county of a firm in a given year, where the specific EWE types included in the calculation are listed in Appendix B.	NOAA Storm
EWE	Lagged standardized value of raw EWEs with a mean of 0 and a standard deviation of 1.	NOAA Storm
Size	Lagged value of the log of total sales (log(sale)).	COMPUSTAT
Salesgrow	Lagged value of the log of sales growth (log(sale/lagged sale)).	COMPUSTAT
ROA	Lagged value of return on asset, defined as income before extraordinary items scaled by total assets (ib/at).	COMPUSTAT
Leverage	Lagged value of debt ratio ((dltt+dlc)/at).	COMPUSTAT
Dividend	Lagged value of cash dividends for common and preferred stock scaled by operating income ((dvc+dvp)/oibdp).	COMPUSTAT
Capexp	Lagged value of capital expenditure scaled by total assets, missing values coded as zeros (capx/at).	COMPUSTAT
R&D	Lagged value of R&D expenses scaled by total assets, missing values coded as zeros (xrd/at).	COMPUSTAT
Adver	Lagged value of advertising expenses scaled by total assets, missing values coded as zeros (xad/at).	COMPUSTAT
Cash	Lagged value of cash balance scaled by total assets (che/at).	COMPUSTAT

Appendix B. Categories and Types of Weather Events in the Definition of the EWE Variable

Event Category	Event Type(s)
Heat event	Heat
	Excessive Heat
Drought	Drought
Wildfire	Wildfire
Flood	Coastal Flood
	Flash Flood
	Flood
	Heavy Rain

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Table 1. Average Climate Strength/Rating and Climate Concern by Industries

This table lists the average climate strength/rating and climate concern by industries as classified by three-digit SIC code. The sample excludes the industries with fewer than five firms and those with at least five firms but the average climate rating is at or less than 0.01.

SIC3	Industry Description	Number of firms	Mean Climate strength/rating	Mean Climate concern
100	Metal mining	30	0.067	0
131	Crude petroleum and natural gas	507	0.162	0.447
138	Oil and gas field services	247	0.016	0.143
204	Grain mill products	49	0.041	0
208	Beverages	118	0.025	0
209	Miscellaneous foods and kindred products	59	0.136	0
211	Cigarettes	26	0.077	0
240	Lumber & wood products (no furniture)	39	0.077	0
252	Office furniture	45	0.244	0
262	Mills, excluding building paper	63	0.063	0
263	Paperboard mills	63	0.048	0
267	Miscellaneous converted paper products	62	0.097	0
281	Industrial inorganic chemicals	117	0.12	0
282	Plastics materials and synthetic	99	0.152	0
283	Drugs	1,250	0.03	0
286	Industrial organic chemicals	80	0.05	0
291	Petroleum refining	130	0.192	0.886
314	Footwear, excluding rubber	71	0.07	0
335	Nonferrous rolling and drawing	96	0.031	0
344	Fabricated structural metal products	64	0.016	0
351	Engines and turbines	40	0.1	0.694
352	Farm and garden machinery	52	0.038	0.565
353	Construction and related machinery	172	0.035	0.195
354	Metalworking machinery	46	0.065	0
355	Special industry machinery	192	0.021	0
357	Computer and office equipment	469	0.03	0
362	Electrical industrial apparatus	100	0.07	0
363	Household appliances	37	0.081	0
366	Communications equipment	363	0.014	0
367	Electronic components and accessories	876	0.031	0
369	Miscellaneous electrical equipment & supplies	102	0.078	0
371	Motor vehicles and equipment	263	0.049	0.261
372	Aircraft and parts	127	0.087	0.093
381	Search and navigation equipment	83	0.048	0
382	Measuring and controlling devices	405	0.037	0
384	Medical instruments & supplies	594	0.012	0
386	Photographic equipment and supplies	32	0.156	0
394	Toys and sporting goods	68	0.044	0
421	Trucking and courier services, excluding air	137	0.036	0
451	Air transportation, scheduled	158	0.025	0.007
491	Electric services	334	0.281	0.714
492	Gas production and distribution	253	0.561	0.066
493	Combination utility services	253	0.451	0.586
499	Cogeneration services & small power producers	25	0.56	0.52
517	Petroleum and petroleum products	18	0.333	0.188
531	Department stores	78	0.038	0
541	Grocery stores	128	0.031	0
550	Retail-auto dealers & gasoline stations	100	0.03	0.677
581	Eating and drinking places	283	0.014	0

594	Miscellaneous shopping goods stores	138	0.051	0
596	Non-store retailers	148	0.034	0
611	Federally & federally-sponsored credit	41	0.049	0
615	Business credit institutions	55	0.073	0
631	Life insurance	192	0.010	0
738	Miscellaneous business services	141	0.014	0
999	Non-operating establishments	58	0.121	0

Table 2. Summary Statistics

This table reports the summary statistics of the major variables in the empirical analysis. The sample is a combination of several databases including KLD STATS, NOAA Storm, and COMPUSTAT, and covers the period between 1997 and 2009. The sample excludes the industries with fewer than five firms and those with at least five firms but the average climate rating is at or less than 0.01, and singleton firms at either the county or industry-year levels. Definitions for all the variables are in Appendix A. Size, Sales growth, ROA, Leverage, Dividend, Capexp, R&D, Adver, and Cash have been winsorized at the 1st and 99th percentiles.

Variable	Observations	Mean	P25	Median	P75	Std
Climate rating	7,706	0.09	0	0	0	0.29
Net CER	7,706	-0.02	0	0	0	0.14
Net CSR	7,706	-0.18	-0.42	-0.17	0.03	0.41
Raw EWE	7,706	4.95	0	3	7	6.62
Heat event	7,706	0.54	0	0	0	1.85
Drought	7,706	0.39	0	0	0	1.70
Wildfire	7,706	0.23	0	0	0	1.60
Flood	7,706	3.92	0	2	5	5.55
Raw EWE (county-level data)	2,534	4.53	0	2	6	6.63
				Between-county std		5.59
				Within-county std		2.87
EWE	7,706	0	-0.75	-0.29	0.31	1
Size (no logs, in $millions)	7,706	4,958.94	355.32	1,221.03	4,356.40	9,986.32
Size	7,706	7.07	5.87	7.11	8.38	1.88
Salesgrow	7,706	0.13	0.02	0.10	0.22	0.27
ROA	7,706	0.02	0.01	0.04	0.08	0.14
Leverage	7,706	0.22	0.04	0.21	0.34	0.19
Dividend	7,706	0.08	0	0	0.13	0.14
Capexp	7,706	0.06	0.02	0.04	0.08	0.06
R&D	7,706	0.05	0	0.02	0.08	0.08
Adver	7,706	0.01	0	0	0	0.03
Cash	7,706	0.19	0.03	0.09	0.28	0.22

Table 3. Extreme Weather and Climate Ratings

This table examines H1 on a positive impact of EWE on climate ratings, conditional on controlling the regional differences in the exposure to EWEs. Panel A presents the *t*-test results on the difference between the (county-demeaned) climate ratings of the firms located in counties with more (county-demeaned) EWEs and those with fewer (county-demeaned) EWEs matched by industry and firm size. Panel B reports the regression results of climate ratings on EWE. The dependent variable for each model is Climate rating. The specific types of EWEs for Heat event, Drought, Wildfire, and Flood are listed in Appendix B. See Appendix A for the definitions of all other variables. Standard errors are adjusted for heteroscedasticity and clustered at both the firm and county-year levels. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: *t*-tests			
	More EWEs	Fewer EWEs	Difference
Observations	2,490	2,490	
Climate rating	0.087	0.076	0.011
	More county-demeaned EWEs	Fewer county-demeaned EWEs	
Observations	2,116	2,116	
County-demeaned Climate rating	0.008	-0.008	0.016**

Panel B: Regression Results						
	(1)	(2)	(3)	(4)	(5)	(6)
EWE	0.007	0.018***	0.015***	0.012***		
	(1.299)	(2.677)	(3.588)	(3.000)		
Heat event					0.007	-0.009
					(1.410)	(-1.210)
Heat event * Southern county						0.022**
						(2.445)
Drought					-0.001	-0.000
					(-0.498)	(-0.075)
Wildfire					0.005*	0.005*
					(1.791)	(1.870)
Flood					0.010***	0.009***
					(3.657)	(3.410)
Net CER				0.158**	0.158**	0.158**
				(2.258)	(2.255)	(2.252)
Net CSR				0.060***	0.060***	0.059***
				(3.195)	(3.197)	(3.176)
Size				0.040***	0.040***	0.040***
				(6.952)	(6.941)	(6.936)
Salesgrow				0.003	0.003	0.002
				(0.214)	(0.217)	(0.194)
ROA				-0.114***	-0.113***	-0.112***
				(-3.878)	(-3.860)	(-3.815)
Leverage				-0.086***	-0.086***	-0.086***
				(-3.301)	(-3.297)	(-3.289)
Dividend				0.101***	0.101***	0.102***
				(2.835)	(2.834)	(2.860)
Capexp				0.373**	0.372**	0.369**
				(2.572)	(2.568)	(2.545)
R&D				-0.120	-0.119	-0.116
				(-1.594)	(-1.582)	(-1.537)
Adver				0.161	0.163	0.175
				(0.700)	(0.706)	(0.760)
Cash				0.046*	0.047*	0.046
				(1.663)	(1.677)	(1.645)

Observations	7,706	7,706	7,706	7,706	7,706	7,706
Industry + Year FE	Yes	Yes	No	No	No	No
Interaction of Industry and Year FE	No	No	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.18	0.29	0.36	0.40	0.40	0.40

Table 4. Test the Recency Hypothesis

This table examines H2 (Recency Hypothesis), which states that recent EWEs have a more pronounced impact on climate ratings than distant ones. EWE_t, EWE_{t-1}, EWE_{t-2}, EWE_{t-3}, EWE_{t-4}, are contemporaneous, one-year lagged, two-year lagged, three-year lagged, and four-year lagged EWE, respectively. Each of these variables is standardized to have a mean of 0 and a standard deviation of 1. The dependent variable for each model is Climate rating. See Appendix A for the definitions of all other variables. All models also include the county FEs and the interactions of year and three-digit SIC industry FEs. Standard errors are adjusted for heteroscedasticity and clustered at both the firm and county-year levels. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
EWE_t		0.010***
		(3.190)
EWE_{t-1}	0.011***	0.009***
	(3.505)	(3.372)
EWE_{t-2}	0.003	0.002
	(0.786)	(0.477)
EWE_{t-3}	0.002	0.001
	(0.587)	(0.466)
EWE_{t-4}	0.002	0.004
	(0.554)	(0.941)
Net CER	0.153*	0.152*
	(1.881)	(1.864)
Net CSR	0.064***	0.065***
	(3.226)	(3.241)
Size	0.042***	0.042***
	(7.279)	(7.277)
Salesgrow	0.000	0.000
	(0.002)	(0.015)
ROA	-0.121***	-0.122***
	(-4.004)	(-4.031)
Leverage	-0.080***	-0.080***
	(-3.018)	(-3.023)
Dividend	0.102***	0.101***
	(2.757)	(2.757)
Capexp	0.368**	0.369**
	(2.445)	(2.452)
R&D	-0.099	-0.098
	(-1.311)	(-1.306)
Adver	0.192	0.190
	(0.766)	(0.756)
Cash	0.050*	0.051*
	(1.825)	(1.833)
Observations	7,011	7,011
Adjusted R^2	0.38	0.38

Table 5. Robustness Tests

This table reports the results to examine the robustness of the relationship between EWEs and climate ratings. Non-zero Climate rating industries is the sample excluding the industries with fewer than five firms and those with at least five firms but the average Climate rating is at or less than 0.01, and singleton firms at either the county or industry-year levels. This has the same exclusion criteria as the primary sample used in the empirical analysis. S&P 500 at 2006 with historical headquarter county information is the sample of the S&P 500 firms at 2006 with the headquarter county data manually collected for the sample period. The other exclusion criteria are the same as the primary sample. Full is the sample with all the industries included. Billion disaster loss is the estimated total normalized state loss by "mega-disasters" causing at least $1 billion inflation-adjusted economic damages in the previous year. The loss of a state is assumed to be proportional to its GDP, and the normalization is based on the GDP at 2009. EWE (no drought) is the EWE variable without drought. The dependent variable for each model is Climate rating. See Appendix A for the definitions of all other variables. Models 1, 2, 4, and 5 also include the interactions of year and three-digit SIC industry FEs. Model 3 also includes the year FEs. Standard errors are adjusted for heteroscedasticity and clustered at both the firm and state-year levels for Model 1, and at both the firm and county-year levels for the other models. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Sample	Non-zero Climate rating industries	S&P 500 at 2006 with historical headquarter county information	Non-zero Climate rating industries	Non-zero Climate rating industries	Full
Model	Linear	Linear	Probit	Linear	Linear
Billion disaster loss	0.003**				
	(2.138)				
EWE		0.024*	0.142***		0.007***
		(1.860)	(2.718)		(3.817)
EWE (no drought)				0.013***	
				(3.761)	
Net CER	0.158**	0.187	-0.250	0.158**	0.158***
	(2.458)	(1.633)	(-0.798)	(2.259)	(2.846)
Net CSR	0.056***	0.058*	0.454***	0.060***	0.033***
	(3.151)	(1.766)	(3.996)	(3.189)	(3.092)
Size	0.047***	0.035**	0.253***	0.040***	0.024***
	(7.972)	(2.285)	(6.440)	(6.955)	(7.639)
Salesgrow	0.008	-0.076*	0.032	0.003	-0.001
	(0.582)	(-1.716)	(0.225)	(0.229)	(-0.079)
ROA	-0.123***	-0.123	-0.755	-0.114***	-0.038**
	(-4.046)	(-0.887)	(-1.559)	(-3.879)	(-2.306)
Leverage	-0.077***	-0.034	0.348	-0.086***	-0.037***
	(-2.859)	(-0.312)	(1.109)	(-3.306)	(-2.788)
Dividend	0.073**	0.315*	1.794***	0.101***	0.033**
	(2.062)	(1.780)	(6.234)	(2.824)	(2.519)
Capexp	0.411***	1.160***	3.414***	0.373**	0.246***
	(2.918)	(2.614)	(4.072)	(2.569)	(2.787)
R&D	-0.029	-0.313	-3.668***	-0.120	-0.044
	(-0.388)	(-0.898)	(-2.705)	(-1.594)	(-0.979)
Adver	0.249	0.421	-6.828**	0.163	0.087
	(1.091)	(0.473)	(-2.370)	(0.707)	(1.012)
Cash	0.086***	-0.060	-0.597	0.047*	0.011
	(3.196)	(-0.562)	(-1.337)	(1.670)	(0.864)
Observations	7,730	2,130	7,706	7,706	17,349
State FE	Yes	No	No	No	No
County FE	No	Yes	Yes	Yes	Yes
Adjusted R^2	0.33	0.49		0.40	0.35
Pseudo R^2			0.28		