Extreme Weather and Ratings on Corporate Climate Mitigation Policies *

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Abstract

This study examines whether the extreme weather events (EWEs) incurred at the headquarters of firms have an impact on their climate mitigation policies. I show that, controlling for county fixed effects, the annual number of EWEs at the headquarter counties of the largest public firms in the US significantly improves the subsequent ratings of their climate mitigation policies, with recent EWEs having a more pronounced impact. I also find that the EWEs at the neighboring counties do not have a similar effect, and provide some evidence that the impact of EWEs on climate ratings is stronger for weakly-governed firms, and that some EWEs positively affect the likelihood of utility firms’ expressing a concern for climate risk through their SEC filings. These results support the idea that personal weather experiences can influence managerial belief in anthropogenic climate change which in turn affects corporate climate mitigation policies.

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1. Introduction

The purpose of this study is to examine whether the extreme weather events (EWEs) incurred at the headquarters of firms have an impact on their climate mitigation policies. Three empirical facts motivate the study. First, despite the overwhelming evidence in support of anthropogenic climate change (ACC) (Cook et al., 2013), there is divergent reception of this issue in the public (e.g., Leiserowitz, Maibach, Roser-Renouf, Rosenthal, & Cutler, 2017), resulting in a failure to enact federal legislations in the US to limit greenhouse gas (GHG) emissions (Arroyo, 2019; Wallach, 2012). Therefore, businesses are mostly on their own to make decisions that can bear serious consequences on future climate. Second, in addition to rising global average temperature, one primary potential consequence of ACC is the increasingly frequent incidences of EWEs such as heat waves, droughts, wildfires, and floods (IPCC, 2012; Melillo, Richmond, & Yohe, 2014), and individual perception of ACC is often shaped by their personal experiences with these EWEs (Bergquist, Nilsson, & Schultz, 2019; Demski, Capstick, Pidgeon, Sposato, & Spence, 2017; Rudman, McLean, & Bunzl, 2013). Third, firm policies often reflect managers’ personal characteristics, values, and beliefs (Bansal & Roth, 2000; Cronqvist, Makhija, & Yonker, 2012; Cronqvist & Yu, 2017; Hambrick, 2007; Hambrick & Mason, 1984; Lawrence & Morell, 1995; Shahab et al., 2020; Sunder, Sunder, & Zhang, 2017; Walls & Hoffman, 2013). If it is reasonable to expect that managers reside in the headquarters of their firms (Pirinsky & Wang, 2010) and, similar to a lay person, are more concerned about ACC after personally experiencing more incidences of EWEs, then the potential “imprinting” of their personal beliefs on corporate policies suggests that the EWEs at the headquarters of the firms may be positively related to their climate mitigation policies.
To examine this Managerial Experiencing Hypothesis (MEH), I use a sample of the largest public firms in the US from 1997 to 2009, a period characterized by rising awareness of ACC in businesses presumably facilitated by the adoption of the Kyoto Protocol, an international treaty to reduce GHG emissions signed by 163 countries (Hoffman, 2006; Kolk, Levy, & Pinkse, 2008; Kolk & Pinkse, 2007; Okereke & Russell, 2010; Wilbanks et al., 2007). I document a positive and significant effect of the annual number of EWEs as sustained in the headquarter county of a firm and its subsequent climate mitigation policies as rated by a third party (abbreviated as climate rating henceforth). Importantly, I show that the significance of the result rests crucially on controlling for county fixed effects (FEs), suggesting the importance of netting out the regional differences in the exposure to EWEs in managerial experiential learning of ACC through EWEs. I also find that recent EWEs have a more pronounced effect on climate ratings than distant ones, which is reflective of a “recency heuristic” in managers’ experiential learning of ACC (Marx et al., 2007).

The fact that I do not directly observe managerial belief suggests that a relation between EWEs and climate ratings may be subject to alternative interpretations. Two notable ones are in order. First, headquarter employees but not managers and/or local stakeholders such as community residents and local NGOs, after witnessing EWEs or suffering great losses from them, may push firms to adopt climate-friendly policies (Local Activism Hypothesis or LAH). Indeed, Dowell, Lyon, and Pickens (2020) document that the climate change belief of community residents matters for the GHG emissions of the local facilities of manufacturing firms. Second, the physical damages caused by the EWEs do not change managerial belief in ACC but cause the replacement of the damaged properties with new ones which coincidently have a lower carbon footprint (Damage
Hypothesis or DH). I conduct several tests to show that, despite the plausibility of these alternative hypotheses, the MEH may still be the most reasonable explanation for the empirical results.

This study contributes to the literature by providing the first large-scale empirical evidence on a positive relationship between the frequency of EWEs at the headquarters of large public firms and their climate ratings. The evidence suggests the importance of proximity to key decision makers of a firm in shaping its corporate policies even in the case of natural forces. For policy makers who are concerned about alleviating the potentially devastating impact of ACC, the results in the study advocate communicating the urgency of taking actions not only through the presentation of climate model forecasts but, more importantly, vivid images and programs that attempt to evoke participants’ memories of climate-related natural disasters.

The paper proceeds as follows: In Section 2, I review the relevant literature and develop the MEH and related Recency Hypothesis (RH). Section 3 presents the data, variables, empirical model, and summary statistics. Section 4 conducts the empirical analysis followed by discussions in Section 5. Section 6 concludes.

2. Literature Review and Hypotheses Development

Given the critical importance of the issue of ACC, the lack of federal legislations suggests that understanding the determinants of firm climate strategies is of utmost importance. The extant studies have looked at factors such as economic incentives (Backman, Verbeke, & Schulz, 2017; Bottcher & Muller, 2015; Damert & Baumgartner, 2018; Hoffman, 2005; Okereke, 2007; Okereke & Russell, 2010; Sullivan & Gouldson, 2017), regulatory and stakeholder pressures (Boiral, Henri, & Talbot, 2012; Bottcher & Muller, 2015; Bryant, Griffin, & Perry, 2020; Cadez, Czerny, & Letmathe, 2019; Damert & Baumgartner, 2018; Hoffman, 2005; Okereke, 2007; Okereke & Russell, 2010; Sullivan & Gouldson, 2017), legitimation (companies’ desire to meet societal and
institutional norms) (Boiral et al., 2012; Damert & Baumgartner, 2018; Hoffman, 2005), technological innovation (Okereke, 2007; Pinkse & Kolk, 2010), corporate governance (Aggarwal & Dow, 2012; Galbreath, 2010), and litigation and reputational risk management (Hoffman, 2005; Wellington & Sauer, 2005). But the role of the personal attributes of managers on climate policies has received little attention. However, both theory and evidence suggest that corporate policies often reflect the personal characteristics of managers, such as their educational background, tenure, age, experiences, and values (Bansal & Roth, 2000; Cronqvist et al., 2012; Cronqvist & Yu, 2017; Hambrick, 2007; Hambrick & Mason, 1984; Lawrence & Morell, 1995; Shahab et al., 2020; Sunder et al., 2017; Walls & Hoffman, 2013). For example, Cronqvist et al. (2012) find that managers are consistent in borrowing patterns both in their house purchases and corporate financing decisions. Walls and Hoffman (2013) document that corporate directors with past environmental experiences set greener environmental policies. Sunder et al. (2017) find that the “sensation seeking” tendency of CEOs leads to better corporate innovations. Cronqvist and Yu (2017) find that internalizing a daughter’s other-regarding preferences motivates a CEO to engage more in corporate social responsibility (CSR), and Shahab et al. (2020) document that CEOs with research and financial expertise improve the sustainable performance and environmental reporting of publicly listed firms in China.

Studies also suggest that managers’ ecological values matter for corporate environmental policies (e.g., Bansal & Roth, 2000; Boiral et al., 2012; Okereke & Russell, 2010). In the context of ACC, theories in cognitive psychology and neuroscience suggest that individual perception of the risk of ACC is shaped by two fundamental information processing systems: analytical and experiential (Marx et al., 2007; Slovic, Finucane, Peters, & MacGregor, 2004). While the former uses algorithms and normative rules such as probability, statistics, formal logic and risk
assessment, the latter operates mainly on personal memories and concrete images (Slovic et al., 2004). Because ACC is derived from more than 100 years’ data and involves sophisticated statistics and modeling (National Research Council, 2010), an accurate understanding of this issue is only possible for a person with strong analytical capabilities. However, most people including presumably most of the professional managers lack these abilities. Thus, despite its scientific nature, analytical processing of statistical information is unlikely to be the only channel for most lay public to fully digest and accept ACC. This gives rise to the importance of other channels such as popular media. But this channel is subject to the issue of bias and trust (Weber, 2010). In this sense, the “seeing is believing” mentality based on personal experiences may play a significant role in individual acceptance of ACC (Galbreath, 2014). Indeed, despite the “unscientific” nature of this practice because of the difficulty to attribute individual EWEs to ACC or natural variability (National Academies of Science, 2016), experiencing these events may still influence people’s perception of ACC. This is particularly true since relative to analytical processing which relies on statistical expression and hence is cognitively costly (Stanovich & West, 1998), experiential processing operates automatically through memories, often involves vivid images, and frequently elicits strong feelings that make the experiences memorable and dominant in information processing (Epstein, 1994; Loewenstein, Weber, Hsee, & Welch, 2001; Sloman, 1996). Because emotions often play a role in managerial decision making (Hoffman & Bansal, 2012), the presumably intense feelings as elicited from the experiences of EWEs have the potential to strengthen or change the beliefs of managers about ACC, and motivate them to take climate mitigative actions (Leiserowitz, 2006).

To materialize this potential, however, managers need to be aware of the connection between EWEs and ACC. Absent this awareness, personal experiences may not result in a concern about
ACC (Whitmarsh, 2008). An awareness of the connection between climate change and more frequent and intense incidences of EWEs is expected given the increasing popularity of this topic in the media (Bojkoff, 2009). In fact, climate change was a fact of organizational life since at least 1995 (Hoffman, 2006; Kolk & Pinkse, 2007; Okereke & Russell, 2010; Wilbanks et al., 2007). The same may not be true for the connection between EWEs and the anthropogenic nature of climate change since this is influenced by social, institutional, cultural, and in particular partisan factors (Hulme, 2009). Nonetheless, empirically we do observe that individuals are more concerned about climate change and intend to take actions to reduce its impact after experiencing EWEs (Bergquist et al., 2019; Demski et al., 2017; Rudman et al., 2013). Therefore, it may also be reasonable to expect that managers will behave similarly on a personal level. If they further attempt to imprint a stronger belief in ACC into corporate policies, then a positive relationship between EWEs at headquarters and firm climate mitigation policies is expected.

Some anecdotal evidence in the literature suggests the plausibility of the mechanisms as described above. For example, based on detailed interviews with five house-builders in the UK, Hertin, Berkhout, Gann, and Barlow (2003) find that direct signals of climate change such as increased flood risk and hotter summer play a role in managerial perception of climate change. Similarly, Bleda and Shackley (2008) argue that experiences with anomalous (significant and frequent) weather events will increase managerial belief in ACC. Galbreath (2014) and Weber (2006) suggest the importance of personal experiences in driving climate actions. In the environmental psychology literature, there is also a significant number of studies demonstrating that individuals express a stronger concern for ACC after experiencing EWEs (e.g., Bergquist et al., 2019; Demski et al., 2017; Rudman et al., 2013).
Though extant climate models predict more frequent incidences of many types of EWEs with ACC, the regional distribution of the EWEs is uneven (IPCC, 2012; Melillo et al., 2014). For example, California has historically suffered more from droughts and wildfires than many other states, while southern regions are more likely to experience heat waves. Therefore, the effect of the frequency of EWEs on climate policies is expected to be dependent on controlling for the regional differences in the exposure to EWEs. Indeed, Haigh and Griffiths (2012) find that “climate surprises” are important in changing business strategies. As mentioned above, Bleda and Shackley (2008) also argue that experiences with anomalous weather events will increase managerial belief in ACC. Galbreath (2014) documents that the regional impact of climate change is important to determine corporate climate strategies. These arguments lead to my first hypothesis:

**Managerial Experiencing Hypothesis (MEH):** Controlling for regional differences, the frequency of the EWEs as experienced by corporate managers is positively associated with corporate climate mitigation policies.

In experiential processing, rare events such as EWEs tend to be underweighted relative to their probabilities of occurrence (Hertwig, Barron, Weber, & Erev, 2004; Hogarth & Einhorn, 1992). This is because by nature rare events happen infrequently, so the chance of their occurring in the recent past is small. Because experiential processing operates through working memories which typically include only the memories from the recent past, rare events are likely to be underweighted. On the other hand, when these events did occur, the same mechanism suggests that the experiential processing system tends to overweigh the probability of their reoccurring given the vivid and recent memories from the intense experiences of these events. This argument suggests that recent EWEs may have a stronger impact on managerial decision making on climate policies than distant ones. Similar “recency effects” have been documented in many studies (e.g.,
Bhootra & Hur, 2013; Dessaint & Matray, 2017; Trotman, Tan, & Ang, 2011). For example, Dessaint and Matray (2017) find that the longer in the past hurricanes had stricken the neighboring counties, the less salient they became, and hence the smaller an effect they had on firm precautionary cash holdings. These arguments lead to my second hypothesis:

**Recency Hypothesis (RH):** More recent EWEs have a stronger effect on corporate climate mitigation policies than more distant ones.

It is notable that a revised version of the attention-based view of the firm to explain corporate climate adaptation may also generate the MEH (Pinkse & Gasbarro, 2019). Specifically, Pinkse and Gasbarro (2019) argue that corporate adaptation to climate change depends on an organizational awareness of and a sense of vulnerability to climate stimuli such as abnormal weather. Because of the need for globally collective action to mitigate the impact of climate change, however, awareness may be more relevant for the formulation of mitigation policies than an assessment of vulnerability. As argued in Pinkse and Gasbarro (2019), there are three factors that determine corporate awareness of climate stimuli: risk perception, perceived uncertainty, and firm knowledge of local ecosystems. Direct experiences with climate stimuli especially in the form of an increasing incidence of EWEs as in this study are one of the main drivers of a high risk perception (Pinkse & Gasbarro, 2019). On the other hand, the uncertainty associated with the perception of the climate stimuli could manifest both through the ambiguity in the anthropogenic nature, and the severity and timing of climate change (Pinkse & Gasbarro, 2019). As argued previously, though ex-ante the acceptance of ACC is influenced by many factors, empirically we do observe that individuals exhibit a higher concern for ACC and more willingness to take mitigation actions after experiencing EWEs (Bergquist et al., 2019; Demski et al., 2017; Rudman et al., 2013). In addition, the fact that firms observe a more frequent incidence of EWEs that is the
focus of the study also implies a decreased uncertainty with respect to the severity and timing of ACC, since an increased frequency of EWEs is consistent with the prediction of the dominant climate models (IPCC, 2012; Melillo, Richmond, & Yohe, 2014). These arguments suggest a decreased perceived uncertainty of climate change when firms experience more frequent incidences of EWEs. A third factor that can moderate risk perception and perceived uncertainty is the knowledge firms possess of local ecosystems (Pinkse & Gasbarro, 2019). However, this factor mainly affects firms’ sense of vulnerability to climate change and for the same reason as explained above may be less relevant for the setting of climate mitigation policies. Therefore, a high risk perception and a decreased perceived uncertainty as a result of witnessing more frequent incidences of EWEs by a firm create an awareness of climate change, which may lead to corporate climate mitigation policies as the MEH predicts.2

It is useful to point out here the difference between experiential processing and a closely related concept in information processing, salience, which refers to the replacement of objective probabilities with subjective decision weights that are determined by the relative prominences of different situations (Bordalo, Gennaioli, & Shleifer, 2013). While experiential processing typically requires direct experiences of an event, the salience theory only involves a recollection of a salient situation which may be provoked by memories from a related experience. Nonetheless, witnessing EWEs may increase the salience of ACC and affect the decision weights similar to what experiential processing of weather information does. Therefore, the two theories may generate similar predictions.

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2 Another prediction of the theory based on the two fundamental information processing systems and the attention-based view of the firm is that changing EWE type may have a more pronounced effect on corporate climate mitigation policies than a more frequent incidence of the same type of EWE, since both theories stress the importance of direct experiences with the climate stimuli and a different type of EWE may be more likely to be noticed by a firm. However, the data on EWEs that I employ in this study does not allow for a full-fledged examination of this prediction. Despite this drawback, I explore the plausibility of this hypothesis in the Internet Supplementary.
3. Method

3.1. Sample

The sample used in the empirical study is an intersection of several databases. To test the two hypotheses, I use a third-party rating as an indicator for a firm’s climate mitigation policies. The ratings data are from the KLD STATS database, which rates the CSR policies of the largest public firms by market capitalization in the US. The database started in 1991 with around 650 firms and expanded to about 3,100 firms in 2003. My KLD data ends in 2012. The data cover more than 60 environmental, social, and governance (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. As detailed in the Internet Supplementary, I focus on the years before 2009 because the definitions of the rating variables have changed significantly since the acquisition of KLD by MSCI in 2010. I also exclude the industries with zero or sparse incidences of climate ratings to consider the industry applicability and potential data collection error of this variable.

The data on EWEs are from the Storm Events Database of the National Oceanic and Atmospheric Administration (NOAA). The financial data are from COMPUSTAT, which also includes the data on headquarter counties. Because this database lists only the headquarters at the date when the data were extracted which were 2006 and 2011 in my case, I assume that the headquarters for the years on or before/after 2006 are the same as those of 2006/2011. Empirically speaking few firms changed headquarters (Pirinsky & Wang, 2006). For robustness I manually collected the data for historical headquarter counties of the S&P 500 firms at 2006 over my sample period and show in the Internet Supplementary that the results are qualitatively similar.
To consider the possibility that some EWEs may have occurred after the climate policy was set in a calendar year, I lag the EWE variable by one year.\textsuperscript{3} Because the coverage of the Storm Database began in 1996, this operation means that the sample starts in 1997. The final sample covers the period between 1997 and 2009 with 7,706 firm-years, 1,526 firms, 56 industries, and 334 headquarter counties.

3.2. Measures

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

3.2.1. Climate Policy and Other CSR Variables

As mentioned I use the KLD ratings as a measure of firm climate policies. These ratings are a binary variable indicating either a strength or a concern. According to the data guide, the strength or concern is assigned a value of one if a firm meets the (proprietary) criteria as established for a rating, and zero otherwise. I focus on the strength rating for the climate policies because the concern rating is only applicable to the most carbon intensive industries (petroleum, utility, and transportation), which implies that managers have little leeway to alter this rating since doing so may mean exiting their industries altogether. In contrast, firms have more discretion to earn a strength rating by means such as generating or using more renewable energy while staying in the same industry. I term the climate strength rating \emph{Climate rating}.

I also create two additional variables from the KLD data to consider that CSR investments are often clustered: one with all the ratings in the environment category other than \emph{Climate rating} (Net Corporate Environmental Responsibility or \emph{Net CER}), and the other with all the CSR ratings in the categories other than environment (\emph{Net CSR}). Because the availability of the KLD variables

\textsuperscript{3} I show in the Internet Supplementary that the results are qualitatively similar if using contemporaneous values of the EWE and control variables.
changes over time, studies have adopted different methods to define Net CER and Net CSR (e.g., Benson & Davidson III, 2010; Cai, Jo, & Pan, 2011; Goss & Roberts, 2011; Harjoto, Jo, & Kim, 2017; Jo & Harjoto, 2012). In my primary specification I follow Benson and Davidson III (2010) to define these two variables, but I show in the Internet Supplementary that the results are robust to other definitions.

3.2.2. Extreme Weather

I measure the strength of EWEs striking the headquarter of a firm as the annual number of EWEs incurred at the headquarter county of the firm (EWE). One concern for using the number of rather than the economic damages caused by EWEs is that some of the EWEs may not be severe enough to induce changes in beliefs. This concern is alleviated by the fact that the NOAA Storm Database records only exceptional meteorological events with the “intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce” (NWS, 2018). The Internet Supplementary lists the weather events that are covered by this database. The database is good at recording transient events such as storms but deficient in the coverage of long-duration events such as droughts. Therefore, I examine the robustness of the results by excluding droughts from the definition of EWE in the Internet Supplementary.

The specific weather events that are used in the definition of EWE are listed in Appendix B, where the events are grouped into four categories: Heat event, Drought, Wildfire, and Flood. These events are predicted to increase with ACC with relatively low uncertainty (Melillo et al., 2014). In the Internet Supplementary, I show the robustness of the results using an alternative definition

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4 Although 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 the Internet Supplementary.

5 The change in the frequency of other EWEs and the extent of their human influences are more uncertain, including hurricanes, tornadoes, hail, thunderstorms, winter storms, and cold spells. In the Internet Supplementary, I examine the impact of other types of EWEs on climate ratings.
of EWE with a more comprehensive list of weather events. To facilitate interpretation, I standardize EWE to have a mean of zero and a standard deviation of one.

3.2.3. Control Variables

Because climate policies are part of CSR, I follow the literature on the determinants of CSR for the control variables in the regressions (Aggarwal & Dow, 2012; Baron, Harjoto, & Jo, 2011; Di Giuli & Kostovetsky, 2014; Jiraporn, Jiraporn, Boeprasert, & Chang, 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 and, similar to EWE, lagged by one year to alleviate the concern for endogeneity.

3.3. Model

The two hypotheses developed in Section 2 require netting out the regional differences in the exposure to EWEs. There are two methods to do this: FEs and de-trending EWE. I employ the FE model for two reasons. First, the “trend” variable is typically calculated from the average value of the variable over the past 10 years or longer period of time (e.g., Egan & Mullin, 2012). In my example this is infeasible because my sample started at the second year after the beginning of the Storm Database. Second, controlling for county FEs also considers, at least to some extent, the influences of other regional unobservable characteristics such as local community engagement in climate change actions and regulatory pressures on firm climate policies.

The KLD data are typically very “sticky” in that the ratings rarely change over time, presumably reflecting the threshold that firms need to overcome to receive a rating. This data feature is likely

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6 Most of the extant studies on the determinants of climate mitigation strategies in the management literature are based on survey data, which is different from the sample in this study. This is the primary reason why I followed the literature on the determinants of CSR for the control variables in the determinants of Climate rating.

7 In the Internet Supplementary, I show that the results are similar if I also include the firm FEs.
to decrease the chance of finding a significant relation between EWEs and climate ratings since the FE models rely on within variations. Therefore, the significant relation that I find may be a conservative estimate of the true relation between EWEs and firms’ climate mitigation policies.

Since the dependent variable, *Climate rating*, is a dummy, it is most appropriate to use a probit or logit model for the empirical analysis. However, nonlinear models suffer from the “incidental parameter” problem with the inclusion of a large number of FEs, which can compromise the consistency of the estimates (Neyman & Scott, 1948). Because controlling for FEs is critical for this study, I use linear models as the primary specification, but use a probit model for robustness in the Internet Supplementary. My primary empirical specification is as follows:

\[
\text{Climate rating}_{i,j,k,t} = \beta_0 + \beta_1 * \text{EWE}_{j,t-1} + \text{Control Variables}_{i,j,k,t-1} \beta_2 + \alpha_j + \mu_k * \tau_t + \epsilon_{i,j,k,t}
\]  

(1)

In the above equation, *Climate rating* is the climate rating of firm *i* headquartered in county *j* and operating in industry *k* in year *t*. *EWE* is the number of EWEs that occurred in county *j* and year *t-1*. *\alpha_j, \mu_k, and \tau_t* are the county, industry, and year FEs, respectively. These controls consider sector and regional affiliations as well as regulatory uncertainty as shown to matter for corporate climate strategies (Boiral et al., 2012; Cadez et al., 2019; Damert & Baumgartner, 2018; Levy & Kolk, 2002). The interaction of industry and year FEs considers the industry-specific shocks in a given year such as the adjustment of rating criteria for some industries (though not as comprehensive as the wholesale adjustment in 2010). I classify industries based on the three-digit SIC code. In the Internet Supplementary, I show that the results are robust to alternative industry classifications. My primary coefficient of interest is *\beta_1*. The standard errors are adjusted for heteroscedasticity and clustered at both the firm (for autocorrelation) and county-year levels (for the possibility that contemporaneous climate policies of neighboring firms may be correlated).
3.4. Summary Statistics

Because of the sparse incidence of climate ratings (the mean climate rating is only 4.2% for the full sample without excluding any industries), the screening criteria as described earlier resulted in about 75%/60% of the industries/firms excluded from the sample. This obviously raises a concern for the representativeness of the study. I conduct two types of checks to help alleviate this concern. First, in the Internet Supplementary I entertain alternative industry exclusions including using the full sample without any exclusions and confirm the robustness of the results. Second, I list the average values of Climate rating by industries in Table 1 to gauge the representativeness of the sample.8

Insert Table 1 about here

The statistics in Table 1 show that despite the exclusions, the sample still covers a relatively wide range of industries. Specifically, except for service industries for which climate ratings may not be applicable (SIC1=8), all other industries as indicated by the one-digit SIC code are represented. It is also interesting to observe that more polluting industries, such as petroleum and utility firms, also have higher incidences of climate ratings. This is consistent with the idea that polluting industries also have more opportunities to adopt clean technologies or increase renewable energy to earn a strength rating (Jo & Na, 2012; Kotchen & Moon, 2012).

Table 2 reports the summary statistics of the major variables. As shown, the incidence of Climate rating is sparse with a mean of only 0.09 and a median of 0 even after the significant industry exclusions. The average annual number of EWEs in the sample is 4.95, with a standard deviation of 6.62. The statistics are similar when using a county-level sample that keeps one observation for all the firms in the same county in a given year, with a mean of 4.53 and a standard deviation of 6.62.

8 The sample size in this table is larger than 7,706, the size of the primary sample in the regression analyses because I do not consider the availability of the control variables in Table 1.
deviation of 6.63. This county-level sample is free of the bias caused by the uneven distribution of headquarters across counties. The statistics also show that out of the standard deviation of 6.63, 5.59/2.87 comes from cross-sectional/within-county variations. The within variation is critical for the implementation of FE models (Zhou, 2001).

Insert Table 2 about here

Table 2 also lists the summary statistics of the four categories of EWEs. The statistics show that heat events and floods are more common than droughts and wildfires. Among the three types of flood events, flash floods are the most common (2.17), followed by floods (0.98) and heavy rain (0.59). The summary statistics for the control variables largely accord with other studies (e.g., Di Giuli & Kostovetsky, 2014; Jiraporn et al., 2014).

4. Empirical Results

4.1. Hypotheses Tests

In this section I test the two hypotheses as developed in Section 2. I first examine the MEH, which predicts that controlling for the regional differences, EWE is positively associated with climate ratings. I use two methods to highlight the importance of demeaning EWE: *t*-tests based on matched samples and regressions. I conduct two types of matching. First, I match firms experiencing more EWEs with those experiencing fewer EWEs (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 climate ratings of the two matched samples are presented in Table 3.

Insert Table 3 about here

The table shows that while the difference between climate ratings is not significant for the sample based mainly on cross-sectional variations of EWEs, it is significant at the 5% level for the
sample based on within-county variations. Therefore, netting out the regional difference in EWEs is important in the relation between EWEs and climate ratings.

In Table 4, I run regressions based on Equation (1) to formally test the MEH. I start with a model with only industry and year FEs in Model 1. The coefficient for 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 the MEH. Instead of controlling for the industry and year FEs individually as in the first two models, I include their interactions in Model 3. The coefficient for EWE is smaller but remains highly significant. In Model 4, I add the control variables. The EWE continues to be highly significant, although 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 CSRs at the same time. Further, firm size is positively associated with climate ratings, suggesting that larger firms are more likely to engage in climate initiatives. This result and the signs on many other control variables accord with the extant literature (e.g., Aggarwal & Dow, 2012; Boiral et al., 2012; Damert & Baumgartner, 2018; Di Giuli & Kostovetsky, 2014; Jiraporn et al., 2014).

Insert Table 4 about here

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

In Model 5, I examine the individual effects of the four categories of EWEs to consider the potentially differential effects of the different types of EWEs on climate ratings. 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 and not significant. The insignificant effect of *Heat event* is a little unexpected since heat waves are probably the most prominent weather event that is associated with climate change. However, the experiences of heat waves in different regions could be different. Specifically, for people from northern regions with colder weather, warming may not feel as bad as people living in the south. To examine this possibility, I create a dummy variable that indicates whether the headquarter is in a southern county based on its latitude. I obtain the latitude data from the 2000 and 2010 Census Gazetteer Files. The *Southern county* dummy equals one if the latitude of the county is at or below the sample median, and zero otherwise. I then interact this variable with *Heat event* in Model 6. Interestingly, the interaction term, *Heat event * *Southern county* is positive and significant. After netting out this term, *Heat event* itself is negative but not significant. This result suggests that while firms headquartered in the south engage more in climate initiatives after experiencing more heat waves, firms in the north do not. Notably, Hsiang et al. (2017) show a possible wealth transfer from southern to northern areas as a result of ACC.

I proceed to examine the RH, which states that more recent EWEs have a more significant impact on climate policies than more distant ones. To do this, I lag *EWE* by one, two, and three years respectively, and control for these additional variables in the regressions. The results are
reported in Table 5. Model 1 shows that among the four EWE variables, only EWE is significant, suggesting that the effects of EWEs on climate ratings dissipate over time, and typically do not last for more than a year. This is consistent with a recency heuristic driving managers to set climate policies after experiencing EWEs. To further examine this hypothesis, I separate the annual number of EWEs into two parts, one for those incurred in the first half of the year (EWE_{half1}), and the other in the second half (EWE_{half2}). If the RH holds, I expect the second EWE variable to be more significant. The results in Model 2 are consistent with this expectation—between the two EWE variables, only EWE_{half2} is significant. As a placebo test, I also separate the three lagged EWE variables into their corresponding first-half-year and second-half-year components in Model 3. The results show that none of these variables is significant. Overall, the results in Table 5 provide support for the RH.

Collectively, the results in Tables 3–5 support the two hypotheses as developed in the study. These results are consistent with the idea that managerial experiential processing of weather information is important to determine corporate climate mitigation policies.

As stated in the introduction, the fact that I do not observe managerial belief directly suggests that these results are amenable to alternative explanations, with the LAH and DH as two prominent ones. The LAH states that the positive effect of EWEs on climate ratings is not driven by managers but local stakeholders (employees, community residents, local NGOs, etc.) who become more concerned about ACC after experiencing more incidences of EWEs. In contrast, the DH argues that the physical damages caused by EWEs to firms’ headquarter properties do not change managerial belief in ACC, but simply result in the damaged properties being replaced by new ones which coincidentally have a lower carbon footprint. However, the fact that the positive and
significant relation between EWEs and climate ratings only holds when county FEIs are controlled for is inconsistent with the prediction of the DH because if it is true, one would expect that this relation should also hold without including the county FEIs since it should be the damage itself rather than its region-demeaned value that matters for the replacement decision. Below I conduct several additional tests to further substantiate the MEH against the two alternative hypotheses.

4.2. EWEs at Neighboring Counties and Climate Ratings

Because the MEH is about experiential learning of ACC through EWEs and if managers’ chance of personally experiencing EWEs decreases with the distance from their firms’ headquarters, it would be reasonable to expect that EWEs incurred at the neighboring counties to a firm’s headquarters count should not matter as much for its climate policy as the EWEs at the headquarters county. I examine this implication of the MEH in the Internet Supplementary, where I document that the EWEs at the neighboring counties do not have a significant effect on the climate rating of a firm. This result provides further evidence that is consistent with experiential learning but inconsistent with the expectation that if the LAH holds, the community residents at the neighboring counties, after suffering from the EWEs, should also attempt to push the firms to engage more in climate mitigation actions. The evidence is also inconsistent with the DH in the sense that since firms in my sample are large, they are likely to have properties in the neighboring counties as well. If the damage to a firm’s facilities drives the positive relation between EWEs and climate ratings, then a similar relation should also exist between the EWEs at the neighboring counties and climate ratings as well.

4.3. Corporate Governance and the Effect of EWEs on Climate Ratings

Since the MEH rests on managers imprinting their personal beliefs in ACC in corporate climate policies, the degree to which managers can do so may depend on the corporate governance of their
firms. It is expected that powerful managers afforded by weak governance should have more discretion to influence policy setting and imprint their personal values (Cronqvist et al., 2012). In the Internet Supplementary I examine this implication of the MEH and obtain some results that are consistent with this expectation. To the extent that powerful managers are insensitive to the demands of the stakeholders of the firm, this evidence is not consistent with the prediction of the LAH. The replacement decision based on the DH should also not be related to the governance strength of a firm.

4.4. EWEs and Managerial Concern for Climate Risk

If it is the managers themselves rather than the local stakeholders of the firms who drive a change in climate policies after abnormal number of EWEs had impacted their local areas, then they may have an incentive to express a concern for climate risk either through media or their financial statements to justify their actions. Similarly, if physical damages rather than managerial learning about ACC drives the relationship between EWEs and climate ratings, then there is no reason to expect managers to be concerned about climate risk. Therefore, examining the effect of EWEs on managerial incentive to express a concern for ACC not only provides direct evidence for the mechanisms underlying the MEH, but also serves as a means to pit the MEH against both the LAH and DH. However, managerial concerns for climate risk may vary with industries. One dominant concern is for potential regulations to limit GHG emissions (Okereke & Russell, 2010). From this perspective, the utility industry may suffer the greatest risk and hence may have the strongest incentive to disclosure the climate risk in their financial statements (Brouhle & Harrington, 2009; Weinhofer & Hoffmann, 2010). In fact, President Barack Obama’s Clean Power Plan of 2015, one of the first major federal initiatives to limit GHG emissions, was directed to the utility industry. For this reason, I focus on the utility industry to examine whether EWEs incurred
at the headquarters can affect the likelihood of managers to express a concern for climate risk in their financial statements.

To do this, I follow Dessaint and Matray (2017) and perform a textual analysis of the public filings of the utility firms (SIC2=49) in the sample. Specifically, I search for expressions such as “risk of climate change,” “risk of global climate change,” and “risk of global warming” in all the 10-Ks, 10-Qs, and 8-Ks filed during the sample period. The sample has 103 firms headquartered in 83 counties, and 734 firm-years. The search resulted in 180 documents. I then look into each document and categorize the mentioning of climate risk into two types: regulatory and managerial. The former refers to the mentioning of the prospect of climate regulations, and the latter refers to managerial self-assessment of climate risk and/or mentioning of taking voluntary actions to mitigate this risk. Note that a single document could include either or both types of mentions. I then define a dummy variable, Climate risk, that equals one if in a given year the firm mentioned climate risk in any of its 10-K/10-Qs/8-Ks, and zero otherwise. Overall, 11% of the firm-years mentioned climate risk, with 94% of them about regulatory risk and 68% about managerial risk. The mentioning of climate risk in financial statements increased over time, perhaps reflecting the increasing awareness of ACC. But even in 2009, the latest year in the sample, only 36% of the firms mentioned climate risk in their public filings. I then run regressions to see whether EWEs at firms’ headquarters positively relate to Climate risk, as would be expected if managers are more

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9 The list of exact expressions I used in the search were: “climate change risk,” “risk of climate change,” “climate change threat,” “threat of climate change,” “threat from climate change,” “possibility of climate change,” “occurrence of climate change,” “likelihood of climate change,” “probability of climate change,” “susceptible to climate change,” “prone to climate change,” “climate change,” “and climate change,” “or climate change,” “risk of global climate change,” “threat of global climate change,” “threat from global climate change,” “possibility of global climate change,” “occurrence of global climate change,” “likelihood of global climate change,” “probability of global climate change,” “susceptible to global climate change,” “prone to global climate change,” “global climate change,” “global warming risk,” “risk of global warming,” “global warming threat,” “threat of global warming,” “threat from global warming,” “possibility of global warming,” “occurrence of global warming,” “likelihood of global warming,” “probability of global warming,” “susceptible to global warming,” “prone to global warming,” “global warming,” “and global warming,” “or global warming”.

Electronic copy available at: https://ssrn.com/abstract=3894744
concerned about ACC after experiencing more incidences of EWEs. The results are reported in Table 6.

I first run regressions on *Climate rating* for this subsample to examine whether the significant effect of EWEs on climate ratings also holds for utility firms. Indeed, Model 1 shows that EWE continues to be positive and significant.\(^\text{10}\) In Model 2 when I break up the EWEs into the four categories of extreme weather as defined earlier, I find that only floods are significantly related to climate ratings. This is in slight contrast to the results based on the full sample (Model 4 in Table 4), where wildfires are also weakly significant. In Model 3, I examine the effect of EWE on *Climate risk*. I utilize a specification that is similar to Equation (1) but with *Climate risk* as the dependent variable. The results show that EWE is positive but not significant. However, similar to what the results in Model 2 suggest, different types of EWEs may have a differential impact on managerial concern for climate risk. Therefore, I control for individual categories of EWEs in Model 4 to gauge this possibility. Interestingly, while the results in Model 2 demonstrate that among the four categories of EWEs only *Flood* is positively and significantly associated with climate ratings, Model 4 shows that only *Flood* positively and significantly (at the 10% level) affects the likelihood of managers’ expressing climate risk in their financial statements. In unreported analysis I also find that the results are similar if the dependent variable is defined over regulatory risk mention or managerial risk mention respectively, the two types of climate risk mentions as defined above. A natural interpretation of these results is that while managers of utility firms are concerned about the climate risk as a reflection of their belief in ACC after experiencing abnormal number of floods, they take corporate mitigative actions to reduce the impact of ACC. It is notable that none of the

\(^{10}\) In unreported analysis, I find that this relation also holds for non-utility firms.
control variables is significant in the two models on Climate risk.\textsuperscript{11} To demonstrate the importance of netting out the regional differences in the exposure to EWEs in the relation between EWEs and managers’ mentioning of climate risk in their financial statements, I omit the county FE in Model 5. Now, Flood loses significance, which is similar to the results with respect to climate ratings and consistent with managerial learning of climate change based on abnormal level of EWEs. Collectively, the results in Table 6 provide some further evidence that is consistent with the MEH but hard to be explained by both the LAH and DH.

In the Internet Supplementary, I conduct three additional tests to examine the implications of the DH and find evidence that is further inconsistent with this hypothesis. By and large, the empirical results as established in the study provide the strongest support for the MEH, despite the plausibility of two alternative explanations based on local stakeholders activism and physical damages caused by EWEs.

5. Discussions

5.1. Contributions of the Study

This study employs a fine level of geographic resolution – headquarter counties, in an attempt to identify managerial personal experiences of EWEs, and studies their impact on corporate climate mitigative policies as measured by KLD ratings. The results show that controlling for county FE, EWEs result in higher climate ratings, and more recent EWEs have a stronger impact. The best explanation for these results out of the three hypotheses considered is that personal experiences with respect to EWEs changes or enhances managerial belief in ACC and, in an

\textsuperscript{11} The large coefficient on R&D is due to the very sparse incidences of positive R&D expenditures for utility firms. Among the 734 firm-years, only two have positive R&D, and the two values are very small. It is also notable that advertising drops out in Table 6 because none of the firms in the sample had any advertising expenditure, which is typical for utility firms.
attempt to imprint this belief into corporate actions, managers set a climate-friendly firm policy that is captured by a third-party rating.

The primary contribution of this study is the documentation of a seemingly robust positive relationship between EWEs at the headquarters of the largest public firms and their climate ratings. Despite the anecdotal evidence as discussed earlier suggesting the importance of personal experiences in the formation of managerial ecological value with respect to ACC (Bleda & Shackley, 2008; Hertin et al., 2003), large scale empirical evidence is lacking to the author’s best knowledge. This is particularly true for large multinational firms as is the case for many firms in this study, since a general perception is that the value of managers’ personal characteristics may be dwindled given the complex parameters through which these firms need to navigate and myriad constraints to which they are subject. However, recent evidence suggests that even for these firms executives’ personal traits may still matter for corporate actions (e.g., Cronqvist et al., 2012; Cronqvist & Yu, 2017; Sunder et al., 2017). This study provides the first large-scale empirical evidence suggesting that managerial belief in ACC as presumably facilitated by directly experiencing EWEs likely plays a role in the formation of corporate climate policies in large public firms, resembling a similar mechanism that has been documented in entrepreneurial firms (Kaesehage, Leyshon, Ferns, & Leyshon, 2019).

Despite the fact that a lack of direct measure for managerial belief especially in connection with personal experiences of EWEs makes the results and explanations as provided in the study to be only suggestive, an uncontroversial message coming out of the study for practitioners is that proximity to key decision makers even for natural forces is critical to drive firm policies. From this perspective, this study provides some evidence to substantiate the claim in Galbreath (2014, p. 100) that “location (or proximity) may be a more important salience attribute than power,
legitimacy or urgency when considering climate change”. In terms of the salience theory, an additional contribution of this study is that direct experiences rather than just awareness of EWEs by managers are critical for firms’ climate mitigation policies, as the insignificant effect of neighboring counties’ EWEs on climate ratings suggests. This result contrasts with Dessaint and Matray (2017) who show that hurricanes striking at neighboring counties raise the salience of the disaster risk for managers who in turn set a higher precautionary cash balance for their firms. Two likely explanations for the different results are the potentially higher salience of hurricanes as compared to the EWEs used in the definition of the primary EWE variable in this study, and the different nature of corporate policies between the two studies. While cash balance is an important firm policy that may affect daily operations of the firm, determining policies to mitigate the impact of global climate change in the absence of regulations is subject to the classical “tragedy of the commons” problem and hence may require a higher sense of urgency, which may be afforded only by managers personally experiencing an abnormal number of natural disasters. A rigorous test for these arguments and other possible explanations for the difference in results, however, is beyond the scope of this study and left for future explorations.

5.2. Study Limitations

There are several limitations to this study. First, as stated above, although I have provided some evidence to suggest that MEH seems to be the most reasonable explanation for the results documented in the study, the fact that managerial belief is not directly observable opens doors for other explanations, which is left for future studies.

Second, ratings are an indirect measure of corporate policies and stated policies also may not result in eventual actions (GS Sustain, 2009). A future study could examine the connection between EWEs and corporate climate mitigation actions such as GHG emissions.
Third, the sample period in the study is relatively old and covers a period that was more than 10 years ago. This data limitation is partly due to the post-2009 changing definitions of the rating variables by MSCI as mentioned above. However, as stated in the introduction, this period is characterized by businesses’ increasing concerns about ACC presumably facilitated by the adoption of the Kyoto Protocol. Although the US was not an eventual signer for this treaty, businesses in the US may still feel the pressure to act. On the other hand, basic probability theory suggests that “weather extremes may change much faster than weather means” (Fankhauser, Smith, & Tol, 1999, p. 71), hence these extreme events may be noticeable much sooner than a rising temperature. From this perspective, this time period may have provided a good setting to examine the relation between EWEs and corporate climate policies given that recent years have witnessed an increasing role of other potential influencers of these policies such as institutional investors (Kruger, Sautner, & Starks, 2020), which may complicate such a relation.

Finally, while the current study is limited by climate mitigation policies, a potential future research topic is to examine the impact of EWEs on firms’ climate adaptation policies/actions. While a significant strand of literature has already begun this inquiry, a large-scale study employing a comprehensive set of industries is lacking to the author’s best knowledge, and may provide a fruitful area for future explorations.

6. Conclusion

The fundamental premise of the study is that managers, similar to a lay person, may be undergoing changes in their beliefs in ACC after experiencing extreme weather that are predicted to increase with climate change. The tendency for managers to imprint their personal values into corporate policies then suggests that firm climate policies will likely reflect their beliefs in ACC, which predicts a positive relationship between EWEs at headquarters which are presumably
experienced by managers and the climate mitigation policies of the firm. The empirical evidence provides some support to these arguments.

A key message emanating from the study is that local impact of climate change is important to drive global climate policies of a firm. This mismatch between the scopes of the problem and a potential driver for the solution poses a significant challenge for humankind to solve the unprecedented issue of ACC, especially given its uneven regional impact. On the one hand, the positive effect of EWEs on climate ratings indicates that experiential learning through EWEs may be effective in motivating some professional managers to change climate policies. On the other hand, because climate change in the years before its most catastrophic impact is uncertain and can well be more pleasant for some time (e.g., Egan & Mullin, 2016), absent other forces, many firms may refrain from taking mitigative actions if their local areas have not experienced a negative change in weather patterns based on the results in the study. Yet the window of opportunity for humankind to avoid or reduce the potentially devastating effect of ACC may well lie in those years.

If simulated experiences have similar effect to real experiences, then one way to encourage more managers to take climate actions is to design some education programs that permit the simulated experiencing of calamitous natural disasters that are predicted to unfold with continued climate change. The effectiveness of this type of program for corporate managers is unknown and is left for future exploration.
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Table 1. Average Climate Rating by Industries

This table lists the average climate rating by industries as classified by three-digit SIC code. The sample excludes the industries with zero or sparse incidences of climate ratings.

| SIC3 | Industry Description                                | Number of firms | Mean Climate rating |
|------|-----------------------------------------------------|-----------------|---------------------|
| 100  | Metal mining                                        | 30              | 0.067               |
| 131  | Crude petroleum and natural gas                     | 507             | 0.162               |
| 138  | Oil and gas field services                          | 247             | 0.016               |
| 204  | Grain mill products                                 | 49              | 0.041               |
| 208  | Beverages                                           | 118             | 0.025               |
| 209  | Miscellaneous foods and kindred products            | 59              | 0.136               |
| 211  | Cigarettes                                          | 26              | 0.077               |
| 240  | Lumber & wood products (no furniture)               | 39              | 0.077               |
| 252  | Office furniture                                    | 45              | 0.244               |
| 262  | Mills, excluding building paper                     | 63              | 0.063               |
| 263  | Paperboard mills                                    | 63              | 0.048               |
| 267  | Miscellaneous converted paper products              | 62              | 0.097               |
| 281  | Industrial inorganic chemicals                      | 117             | 0.12                |
| 282  | Plastics materials and synthetic                    | 99              | 0.152               |
| 283  | Drugs                                               | 1,250           | 0.03                |
| 286  | Industrial organic chemicals                        | 80              | 0.05                |
| 291  | Petroleum refining                                  | 130             | 0.192               |
| 314  | Footwear, excluding rubber                          | 71              | 0.07                |
| 335  | Nonferrous rolling and drawing                      | 96              | 0.031               |
| 344  | Fabricated structural metal products                | 64              | 0.016               |
| 351  | Engines and turbines                                | 40              | 0.1                 |
| 352  | Farm and garden machinery                           | 52              | 0.038               |
| 353  | Construction and related machinery                  | 172             | 0.035               |
| 354  | Metalworking machinery                              | 46              | 0.065               |
| 355  | Special industry machinery                          | 192             | 0.021               |
| 357  | Computer and office equipment                       | 469             | 0.03                |
| 362  | Electrical industrial apparatus                      | 100             | 0.07                |
| 363  | Household appliances                                | 37              | 0.081               |
| 366  | Communications equipment                            | 363             | 0.014               |
| 367  | Electronic components and accessories               | 876             | 0.031               |
| 369  | Miscellaneous electrical equipment & supplies       | 102             | 0.078               |
| 371  | Motor vehicles and equipment                        | 263             | 0.049               |
| 372  | Aircraft and parts                                  | 127             | 0.087               |
| 381  | Search and navigation equipment                     | 83              | 0.048               |
| 382  | Measuring and controlling devices                  | 405             | 0.037               |
| 384  | Medical instruments & supplies                      | 594             | 0.012               |
| 386  | Photographic equipment and supplies                 | 32              | 0.156               |
| 394  | Toys and sporting goods                             | 68              | 0.044               |
| 421  | Trucking and courier services, excluding air        | 137             | 0.036               |
| 451  | Air transportation, scheduled                       | 158             | 0.025               |
| 491  | Electric services                                  | 334             | 0.281               |
| 492  | Gas production and distribution                     | 253             | 0.561               |
| 493  | Combination utility services                        | 253             | 0.451               |
| 499  | Cogeneration services & small power producers       | 25              | 0.56                |
| 517  | Petroleum and petroleum products                    | 18              | 0.333               |
| 531  | Department stores                                   | 78              | 0.038               |
| 541  | Grocery stores                                      | 128             | 0.031               |
| 550  | Retail-auto dealers & gasoline stations             | 100             | 0.03                |
| 581  | Eating and drinking places                         | 283             | 0.014               |
| 594  | Miscellaneous shopping goods stores                 | 138             | 0.051               |
| 596  | Non-store retailers                                 | 148             | 0.034               |

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| Code | Description                          | Value | Percentage |
|------|--------------------------------------|-------|------------|
| 611  | Federally & federally-sponsored credit | 41    | 0.049      |
| 615  | Business credit institutions          | 55    | 0.073      |
| 631  | Life insurance                       | 192   | 0.010      |
| 738  | Miscellaneous business services       | 141   | 0.014      |
| 999  | Non-operating establishments          | 58    | 0.121      |
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 zero or sparse incidences of climate ratings, 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   |
| 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   |

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Table 3. Extreme Weather and Climate Ratings (t-tests)

This table employs $t$-tests and matched samples to examine the MEH (Managerial Experiencing Hypothesis) on a positive impact of EWE on climate ratings conditional on controlling for the regional differences in the exposure to EWEs. The two samples are obtained by matching firms headquartered in counties incurring more (county-demeaned) EWEs with those incurring fewer (county-demeaned) EWEs by industry and firm size. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| More EWEs | Fewer EWEs | Difference |
|-----------|------------|------------|
| Observations | 2,490 | 2,490 | 0.011 |
| Climate rating | 0.087 | 0.076 | **0.019** |

More county-demeaned EWEs Fewer county-demeaned EWEs
Table 4. Extreme Weather and Climate Ratings (Regressions)

This table employs regression models to examine the MEH (Managerial Experiencing Hypothesis) on a positive impact of EWE on climate ratings conditional on controlling for the regional differences in the exposure to EWEs. 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.

| EWE       | (1)    | (2)    | (3)    | (4)    | (5)    | (6)    |
|-----------|--------|--------|--------|--------|--------|--------|
| Heat event| 0.007  | 0.018***| 0.015***| 0.012***|
|           | (1.299)| (2.677)| (3.588)| (3.000)|        |        |
| Heat event * | 0.007  | 0.009   |
| Southern county | (1.383)| (-1.237)|        |        |        |        |
| Drought   | -0.002 | -0.000  |
|           | (-0.533)| (-0.102)|        |        |        |        |
| Wildfire  | 0.005* | 0.005*  |
|           | (1.795)| (1.867) |        |        |        |        |
| Flood     | 0.009***| 0.009***|
|           | (3.401)| (3.206) |        |        |        |        |
| Net CER   | 0.158**| 0.158**|
|           | (2.258)| (2.252) | (2.249)|        |        |        |
| Net CSR   | 0.060***| 0.060***|
|           | (3.195)| (3.196) | (3.175)|        |        |        |
| Size      | 0.040***| 0.040***|
|           | (6.952)| (6.940) | (6.934)|        |        |        |
| Salesgrow | 0.003  | 0.003   |
|           | (0.214)| (0.224) | (0.200)|        |        |        |
| ROA       | -0.114***| -0.113***|
|           | (-3.878)| (-3.856) | (-3.811)|        |        |        |
| Leverage  | -0.086***| -0.086***|
|           | (-3.301)| (-3.302) | (-3.293)|        |        |        |
| Dividend  | 0.101***| 0.101***|
|           | (2.835)| (2.834) | (2.859)|        |        |        |
| Capexp    | 0.373**| 0.373**|
|           | (2.572)| (2.569) | (2.546)|        |        |        |
| R&D       | -0.120 | -0.119  |
|           | (-1.594)| (-1.581) | (-1.537)|        |        |        |
| Adver     | 0.161  | 0.162   |
|           | (0.700)| (0.704) | (0.759)|        |        |        |
| Cash      | 0.046* | 0.047*  |
|           | (1.663)| (1.674) | (1.642)|        |        |        |
| 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 R² | 0.18   | 0.29   | 0.36   | 0.40   | 0.40   | 0.40   |

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Table 5. Test the Recency Hypothesis

This table examines the RH (Recency Hypothesis), which states that recent EWEs have a more pronounced impact on climate ratings than distant ones. EWE\(_{t-1}\), EWE\(_{t-2}\) and EWE\(_{t-3}\) are one-year lagged, two-year lagged, and three-year lagged EWE, respectively. The subscript “fhalf”/“shalf” indicates the first/second half of the corresponding year. Each of these variables is standardized to have a mean of 0 and standard deviation of 1. The dependent variable for each model is Climate rating. All models also include control variables as in Table 4, 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)       | (3)       |
|----------------|-----------|-----------|-----------|
| EWE            | 0.011***  |           |           |
|                | (3.505)   |           |           |
| EWE\(_{fhalf}\) |           | 0.001     | 0.002     |
|                |           | (0.583)   | (0.548)   |
| EWE\(_{shalf}\) |           | 0.011***  | 0.011***  |
|                |           | (3.406)   | (3.351)   |
| EWE\(_{t-1}\) | 0.003     | 0.003     |           |
|                | (0.786)   | (0.853)   |           |
| EWE\(_{t-2}\) | 0.002     | 0.002     |           |
|                | (0.587)   | (0.634)   |           |
| EWE\(_{t-3}\) | 0.002     | 0.003     |           |
|                | (0.554)   | (0.740)   |           |
| EWE\(_{t-1, fhalf}\) |         |           | -0.001    |
|                |           |           | (-0.243)  |
| EWE\(_{t-1, shalf}\) |         |           | 0.005     |
|                |           |           | (1.455)   |
| EWE\(_{t-2, fhalf}\) |         |           | 0.004     |
|                |           |           | (0.787)   |
| EWE\(_{t-2, shalf}\) |         |           | -0.001    |
|                |           |           | (-0.433)  |
| EWE\(_{t-3, fhalf}\) |         |           | 0.001     |
|                |           |           | (0.231)   |
| EWE\(_{t-3, shalf}\) |         |           | 0.003     |
|                |           |           | (1.074)   |
| Observations   | 7,011     | 7,011     | 7,011     |
| Adjusted R\(^2\) | 0.38      | 0.38      | 0.38      |
Table 6. Extreme Weather and Managerial Concern for Climate Risk of Utility Firms

This table examines the effect of extreme weather on managerial concern for climate risk as reflected in financial statements (10-K, 10-Q, or 8-K) of utility firms. Climate risk is a dummy variable that equals one if managers mentioned climate risk in their financial statements, and zero otherwise. See Appendix A for the definitions of all other variables. All models also include 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. *-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| Dependent variable | (1)         | (2)          | (3)          | (4)          | (5)          |
|--------------------|-------------|--------------|--------------|--------------|--------------|
|                    | Climate rating | Climate rating | Climate risk | Climate risk | Climate risk |
| EWE                | 0.041**     | 0.020        |              |              |              |
|                    | (1.989)     | (1.133)      |              |              |              |
| Heat event         | -0.007      |              | -0.009       | -0.001       |
|                    | (-0.422)    |              | (-1.222)     | (-0.091)     |
| Drought            | -0.006      |              | -0.010       | -0.011       |
|                    | (-0.494)    |              | (-1.009)     | (-1.409)     |
| Wildfire           | 0.007       |              | 0.001        | -0.007       |
|                    | (0.762)     |              | (0.093)      | (-0.884)     |
| Flood              | 0.057**     |              | 0.042*       | -0.012       |
|                    | (2.608)     |              | (1.827)      | (-0.852)     |
| Net CER            | -0.150      | -0.144       | -0.160       | -0.154       |
|                    | (-0.752)    | (-0.716)     | (-1.219)     | (-1.183)     |
| Net CSR            | -0.079      | -0.079       | -0.007       | -0.007       |
|                    | (-1.041)    | (-1.060)     | (-0.144)     | (-0.140)     |
| Size               | -0.085      | -0.084       | -0.007       | -0.006       |
|                    | (-1.509)    | (-1.488)     | (-0.215)     | (-0.182)     |
| Salesgrow          | 0.023       | 0.030        | 0.006        | 0.013        |
|                    | (0.255)     | (0.334)      | (0.123)      | (0.250)      |
| ROA                | -2.058**    | -2.119**     | -0.864       | -0.908       |
|                    | (-2.371)    | (-2.447)     | (-1.014)     | (-1.073)     |
| Leverage           | -0.526      | -0.566       | -0.098       | -0.077       |
|                    | (-1.343)    | (-1.462)     | (-0.388)     | (-0.317)     |
| Dividend           | -0.145      | -0.164       | -0.243       | -0.262       |
|                    | (-0.803)    | (-0.897)     | (-1.526)     | (-1.632)     |
| Capexp             | -0.977      | -1.016*      | -0.017       | -0.057       |
|                    | (-1.633)    | (-1.705)     | (-0.060)     | (-0.197)     |
| R&D                | 56.561      | 42.032       | 42.318       | 27.621       |
|                    | (0.856)     | (0.624)      | (1.105)      | (0.769)      |
| Cash               | 0.386       | 0.414        | -0.189       | -0.156       |
|                    | (0.590)     | (0.635)      | (-0.389)     | (-0.327)     |
| Observations       | 734         | 734          | 734          | 734          |
| County FE          | Yes         | Yes          | Yes          | Yes          |
| Adjusted R²        | 0.57        | 0.57         | 0.34         | 0.34         | 0.14         |

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## Appendix A. Variable Definitions

| Variable     | Definition                                                                                                                                                                                                 | Data Source |
|--------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------|
| Climate 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  |
| 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 standard deviation of 1.                                                                                                                                                                                      | NOAA Storm  |
| Size         | Lagged value of the log of total sales (log(sale)).                                                                                                                                                                                                                  | COMPUSAT    |
| Salesgrow    | Lagged value of the log of sales growth (log(sale/lagged sale)).                                                                                                                                                                                                   | COMPUSAT    |
| ROA          | Lagged value of return on asset, defined as income before extraordinary items scaled by total assets (ib/at).                                                                                                                                                         | COMPUSAT    |
| Leverage     | Lagged value of debt ratio ((dltt+dlc)/at).                                                                                                                                                                                                                       | COMPUSAT    |
| Dividend     | Lagged value of cash dividends for common and preferred stock scaled by operating income ((dvc+dvp)/oibdp).                                                                                                                                                           | COMPUSAT    |
| Capexp       | Lagged value of capital expenditure scaled by total assets, missing values coded as zeros (capx/at).                                                                                                                                                                 | COMPUSAT    |
| R&D          | Lagged value of R&D expenses scaled by total assets, missing values coded as zeros (xrd/at).                                                                                                                                                                         | COMPUSAT    |
| Adver        | Lagged value of advertising expenses scaled by total assets, missing values coded as zeros (xad/at).                                                                                                                                                                  | COMPUSAT    |
| Cash         | Lagged value of cash balance scaled by total assets (che/at).                                                                                                                                                                                                  | COMPUSAT    |
### 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             |
4. Changing Definitions of Climate Change Related Ratings in KLD

There are two climate change related policy ratings in the KLD STATS Database: climate strength (env_str_d) and climate concern (env_con_f). Table I1 lists the definitions of these two variables over time. It can be seen that climate concern is mainly an industry-based variable, especially before 2012. As such firms have little leeway to change this rating unless changing their industries. Following the acquisition of KLD by MSCI in 2010, the definition of the strength rating underwent a dramatic change. In fact, climate strength was called “Clean Energy” before 2010. After 2010, the definition of this variable was expanded to apply to more industries/companies. The change in the definition of the strength rating is apparent from Figure I1, which shows the time trend of this variable. The figure shows that the average climate strength rating experienced a jump in 2010. Therefore, I focus on the strength rating before 2010 as my primary dependent variable to allow for more years in the panel (as compared to focusing on the years after 2010 with only three years’ data).

Specifically, the 2011 user guide stated that one of the changes in the definitions of the KLD variables was the “introduction of industry specific ESG ratings templates for each of the seven ESG ratings categories.” Starting from 2010, MSCI assigned a “NR (Not Rated)” if a specific rating is not relevant for an industry. This marking means that prior to 2010 KLD did not consider the industry applicability of its ratings. Thus, a climate rating of “0” may mean either that the firm did not meet the criteria for friendly climate mitigation policies to qualify for the strength rating,

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12 The slight downward shift of climate strength between 2001 and 2003 could be explained by the expansion of the KLD database to include smaller firms after 2000. As I show in the main text, firm size is positively associated with climate strength ratings.
or the rating was not applicable to the firm’s industry at all. For example, many service industries (SIC1=8) have “0” climate ratings throughout the sample period. These ratings may indicate that firms in these industries do not engage sufficiently in efforts to mitigate climate change to earn a strength rating. But another possibility is that mitigating climate change may not be relevant for many of these industries, such as health, legal, educational and management services. If this is true, including these industries in the sample is likely to introduce noise to the empirical analysis and decrease the power of the test. This issue would be solvable if the post-2009 data included an accurate classification of industries with consistent “NR” markings, so that I could backtrack the industries in the prior years to determine the applicability of the climate rating. Unfortunately, I find that MSCI did not issue “NR” until 2012 and, more importantly, the “NR” marking is not consistent across firms in the same industry in many cases. For example, while MSCI assigns a “NR” to hhgreggg, Inc., a retail chain of consumer electronics, it gives a rating of “1” to Best Buy, another retailer of electronics products. This kind of inconsistency is prevalent. Actually, around one third of the industries as covered by MSCI in 2012 have inconsistent classifications.

To consider the industry applicability of climate ratings during my sample period, I exclude the industries with zero or very sparse incidences of climate ratings, or industries with very few firm-years. Industries with zero incidence of climate ratings during the entire sample period are excluded because the climate rating is not likely to be applicable to these industries. Industries with a sparse incidence of climate ratings are excluded to consider the possible coding error by KLD. For example, if over the entire sample period only one firm-year out of a 100-firm-year industry has ever received a climate strength rating, this is likely due to an error in data collection. Specifically, I exclude industries whose average Climate rating is less than 0.01. Finally, industries whose number of firm-years is fewer than five are excluded because the small sample makes it
difficult to determine the true incidence of climate ratings for these industries. It turns out, since the incidence of climate ratings is sparse (the mean climate rating is only 4.2% for the full sample without excluding any industries or firms), these screenings excluded a significant number of industries and firms. Specifically, about 75%/60% of the industries/firms are excluded from the sample. Therefore, in the next section I examine alternative samples to check the robustness of the results.

5. Alternative Samples

In the main text I excluded around 75%/60% of the industries/firms from the sample to consider the industry applicability of the KLD ratings. Here I entertain alternative industry exclusions to examine the robustness of the results. The results are reported in Table I2. In Model 1 I use the full sample without any exclusions. As mentioned in the main text, the average value of Climate rating in this case is only 4.2%, which is consistent with a very sparse incidence of climate strength ratings in the KLD data. The results show that EWE continues to be positive and highly significant, though the coefficient becomes smaller. However, because as compared to the primary sample the average value of Climate rating for the full sample decreases significantly (from 0.09 to 0.042), the economic significance of the results actually increases. Specifically, for one standard deviation increase in the annual number of EWEs at the headquarter county of the average firm in the sample (2.65), the coefficient on EWE in Model 1 (0.007) suggests that climate rating will be upgraded by 0.002889 (=0.007*2.65/6.42) notch, which represents a 6.88% improvement in its rating.

The industry applicability of climate rating would not be an issue if MSCI issued consistent “NR” (Not Rated) markings for all the industries after 2009 when it changes the definition of this variable significantly. If this were the case, I would have been able to backtrack all the industries in the pre-2009 period if they received “NR” after 2009. Unfortuantely this is not the case. MSCI
did not start to issue “NR” until 2012 and, more importantly, it did not issue consistent “NR” for all the firms in the same industry. For example, some firms in a given industry may receive a “NR” which, according to the data guide, should suggest that climate rating is not applicable to these firms’ industry. However, the data suggest this is not the case - other firms in many of these industries actually receive either a “1” or “0” rating. This inconsistency introduces further noise into the analysis. In light of this, I entertain three types of industry exclusions to construct samples to check the robustness of the results. First, I ignore the consideration of inconsistency in “NR” markings, and exclude all the industries which received a “NR” for at least one of their firms at 2012 from the sample. It turns out that this exclusion is very significant. The sample size after the exclusions is only 7,193, which is even smaller than that based on the exclusion criteria I applied for the primary sample (7,706). However, the regression results as reported in Model 2 of Table I2 show that EWE continues to be positive and significant. The sample for Model 3 is based on excluding all the industries which have a consistent “NR” marking at 2012. Because of the large number of inconsistent “NR” markings, this exclusion criterion is not restrictive at all as is apparent from the sample size (17,276), which is only slightly smaller than the full sample (17,349). As expected, the regression results are also similar to those based on the full sample. Because some industries may have a strength rating (Climate rating = 1) between my sample period (from 1997 to 2009) even though they are consistently marked as “NR” by MSCI at 2012, I also consider this type of inconsistency in Model 4 and exclude an industry only if it is consistently marked as “NR” at 2012 and does not have a “1” rating for any of its firms between the sample period. Naturally, because of an even smaller number of industries/firms being excluded, the sample size in this case is even closer to that of full sample. The regression results as shown in Model 4 are also similar.
As described in Section 3 of the main text, one drawback of the COMPUSTAT data is that it has only 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 2,160 firm-years. Model 5 in Table I2 reports the results. As shown, EWE continues to be positive and significant though the significance level has decreased, presumably due to smaller sample size. However, the coefficient on EWE is larger.

3. Alternative Definitions of EWE

I employ the NOAA Storm database to construct the EWE variable in the study. In my primary definition of EWE I focus on the four categories of weather events that are closely associated with climate change, namely, heat waves, droughts, wildfires, and floods. As mentioned in the main text, one drawback of the Storm database is that while it is good at recording intense but transient weather events (hurricanes, floods, heat waves, etc.), it is relatively deficient in the coverage of long-duration events such as drought. To examine the robustness of the results, I exclude drought from the construction of the EWE variable in Model 1 of Table I3. It turns out that this operation does not affect the sign and significance of the results.

In addition to the four categories of weather events as included in the definition of EWE, the extant climate models also predict that other EWEs such as hurricanes, tornadoes, and winter storms may also be affected by ACC, though with more uncertainties (Melillo, Richmond, & Yohe, 2014). Therefore, I examine the robustness of the results in Model 2 of Table I3 by including a more comprehensive list of weather events in the definition of the EWE variable (EWE1). The specific types of EWEs in the definition of EWE1 are listed in Table I4.13 These events largely fall

13 The database also covers lakeshore flood, marine hail, marine high wind, marine strong wind, and marine thunderstorm wind. However, there are no incidences of these events in my sample, and hence I do not list them in the table.
into 8 categories: heat events (including droughts and wildfires), floods, winter weather, tropical storms (including hurricanes), wind events, hails, lightnings, and tornadoes. As can be seen from Model 2, the coefficient on EWE1 is positive and highly significant, and much larger than what is reported in Model 4 of Table 4 in the main text. In untabulated analysis, however, I do not find that the coefficient on EWE and the difference between EWE1 and EWE to be statistically different when controlling both in the regression.

In models 3 & 4 I examine the types of EWEs that are associated with ACC with even less certainties (IPCC, 2012a). Specifically, I consider cold events that are the sum of the annual numbers of cold/wind chill, extreme cold/wind chill and frost/freeze events as in Table I4. At first glance this seems to be the opposite of heat events as studied in the main text. That is, while heat waves are expected to increase with ACC, cold weather must be expected to decrease with it. Closer examination of climate models, however, suggests this is not the case. The change in the incidence of extremely cold weather as a result of climate change is actually uncertain. This uncertainty is driven by the fact that while an increase in mean temperature implies a decrease in the incidence of cold weather, an increase in the variance and/or a shift in the shape of the probability distributions of temperatures that are possible in ACC, can result in an increase in cold weather (IPCC, 2012a, p. 7 & 121). Therefore, the change in cold events with ACC is ambiguous.

Complicating this ambiguity further is the uncertainty of managerial knowledge of the implications of ACC on the incidence of cold weather. If managers understand climate change as implying an increase in heat events and a decrease in cold spells, then experiencing more cold weather will lower their confidence in ACC and decrease their incentives to take mitigation actions. On the other hand, if managers understand the inherent uncertainty associated with the change in cold weather as a result of ACC as the discussion on climate models above suggests,
experiencing more cold weather is possible to enhance their belief in ACC and increase their incentive to adopt climate mitigation policies. Indeed, there is some evidence suggesting that individuals are more concerned about climate change after experiencing abnormally cold weather (e.g., Brooks, Oxley, Vedlitz, Zahran, & Lindsey, 2014; Capstick & Pidgeon, 2014; Lang, 2014).

The results in models 3 & 4 confirm the complexity of the relation between cold spells and climate ratings: while on average cold weather is positively associated with climate ratings as Model 3 demonstrates, the effects of different types of cold weather are not consistent as Model 4 shows. Specifically, both cold/wind chill and frost/freeze are significant, but in opposite directions. In untabulated analysis, I further consider other EWEs in Table I4 that are also cold-related, including blizzard, heavy snow, ice storm, lake-effect snow, sleet, winter storm, and winter weather. The results are similar. In particular, none of these winter weather related EWEs is individually significant, but the total sum of the three cold events as studied in Table I3 and these events is positive and significant. Note that this latter group of cold events is part of EWE1, and all of them are associated with water vapor in the atmosphere, which may increase as a result of ACC (IPCC, 2012b).

By and large, the results with respect to cold EWEs as reported in Table I3 are harder to interpret than the results with respect to heat events in Table 4 of the main text. This provides another reason to focus on the types of EWEs that are associated with ACC with less uncertainty which is what is currently done. This can help alleviate the ambiguity with respect to managers’ knowledge base.

4. Using Economic Damages to Measure EWE

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 $1 billion inflation adjusted damages (Smith & Katz, 2013). I assume that the damage of a state is proportional to its GDP. I then sum up the estimated damages of all the disasters affecting the state in the previous year, and “normalize” this variable using the 2009 state GDP. The normalization takes account of the different levels of wealth at stake at different point in time (e.g., Pielke Jr. et al., 2008; Simmons, Sutter, & Pielke Jr., 2013). One of the downsides of this disaster variable is its coarser geographic resolution. I examine the relationship between this economic damage variable and climate ratings in Model 3 of Table I3. To be consistent with the state-level disaster variable, I replace the county FE$s with the state FE$s, 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.

5. Contemporaneous Values of EWE and Control Variables

The primary specification employs one-year lagged values for all the independent variables including the primary variable of interest, EWE. The rationale for using the lagged EWEs is to consider the possibility that climate policies may be determined in the middle of a year even though climate rating is reported at the end of the year, hence some EWEs that happened after the determination of the policy should not matter for managerial experiential learning of ACC. The inclusion of the lagged control variables is to alleviate the concern for endogeneity. Here I examine the robustness of the results by using the contemporaneous values of all these variables. This enables the sample to include the starting year of the Storm Database, 1996. Hence the final sample

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14 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 EWE. 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.
covers the years from 1996 to 2009 with 9,481 firm-year observations. The regression results are presented in Model 4 of Table I3. As shown, $EWE_t$ (contemporaneous value of EWE) continues to be positive, though the significance becomes slightly weaker at the 10% level.

6. **Alternative Definitions of Net CER/CSR**

The literature has employed different methods to define the net rating of a firm’s CSR. In my primary analysis I follow Benson and Davidson III (2010) to define Net CER/CSR. I examine the robustness of the results in this section using other definitions. I first follow Harjoto, Jo, and Kim (2017) to consider the industry-specificity of CSR, and define Net CER/CSR as the net environmental/social score (total strength count – total concern count) minus the minimum value of this score in the firm’s industry, scaled by the industry range (maximum – minimum) of this score. Results using these measures of Net CER/CSR are reported in Model 1 of Table I5. The coefficient on EWE continues to be positive and significant. Interestingly, Net CER based on this definition loses significance. In untabulated analysis, I define other measures of Net CER/CSR by following Goss and Roberts (2011), Jo and Harjoto (2012), and Cai, Jo, and Pan (2011), respectively. The results are also similar.

7. **Probit Model**

Because the dependent variable, Climate rating, is a dummy variable, it is more appropriate to use a nonlinear model than the linear model I employ in the paper. As discussed in the main text, however, the critical importance of controlling for a large number of FEs in the model jeopardizes the consistency of nonlinear models due to the “incidental parameter” problem (Neyman & Scott, 1948). Here I employ a probit model to examine the robustness of the results, but only control for county and year FEs in light of the incidental parameter problem. The results as reported in Model
2 of Table I5 show that EWE continues to be positive and highly significant, suggesting that the major findings in the paper are not sensitive to model specifications.

7. Firm FEs

In my primary specification I include county and industry-year FEs. But some unobserved firm-level characteristics may also help determine climate policies, such as corporate culture. If these firm-specific unobservable characteristics do not change over time, they could be captured by a firm FE. Therefore, I examine the robustness of the results by further including the firm FEs in the regression model. The results are reported in Model 3 of Table I5. As it turns out, controlling for these unobservable time-invariant firm attributes makes the coefficient on EWE to be even larger.

8. Alternative Industry Classifications

In my primary empirical analysis I classify industries based on three-digit SIC code. I check the robustness of the results by different industry classifications in this section. I consider four classifications: four-digit SIC code, two-digit SIC code, Fama-French 48 industries, and Fama-French 12 industries (Fama & French, 1997). I then interact each of these four types of industry dummies corresponding to these classifications with year dummies respectively in the regressions. The results are reported in Table I6, and demonstrate that a positive and significant impact of EWEs on climate ratings is robust to different industry classifications.

9. EWEs at Neighboring Counties and Climate Ratings

As a placebo test, in Table I7 I examine whether the EWEs at the counties neighboring to the headquarter county of a firm have a different impact on its climate rating as compared with the EWEs at the headquarter county of the firm. Because experiential processing is often associated with strong affect, compared to the possibly vicarious nature of the EWE experience in the

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15 I thank Kenneth French for providing the details of the Fama-French 48 and 12 industry classifications in his website at: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
neighboring counties, the affect associated with the personal experiencing of EWEs at the headquarter county may be stronger. Indeed, there is some evidence from the environmental psychology literature that direct experience of natural hazards is more powerful than vicarious experience to increase the concern of an individual for climate change (Lujala, Lein, & Rod, 2015). As a result, it may be reasonable to expect that the EWEs at the neighboring counties may not generate as strong an impact on climate ratings as the EWEs presumably experienced personally by managers at their headquarter counties. I employ two methods to identify the neighboring counties. In Models 1 and 2 of Table 17, I identify a neighboring county based on whether its distance from the headquarter county is within a certain range. If multiple counties meet this criterion I take the average of their annual frequencies of EWEs. A second method to identify a neighboring county, which is used in Model 3, is to rank the distances from all the neighboring counties to the headquarter county. I then include the annual number of EWEs at the four closest neighboring counties respectively.

Models 1 and 2 consider two sets of ranges, a coarser set with ranges between 0 and 200km, and between 200km and 400km; and a finer set to further divide each of these two ranges into two equal sub-ranges. The results show that none of the EWE variables corresponding to the neighboring counties is significant. One possibility is that managers may be more affected by the maximum number of EWEs across all the neighboring counties than their average because the maximum may be more salient. However, I find similar results if defining the EWE variable at the neighboring counties as the maximum value of EWEs among all the neighboring counties. The

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16 I use the Haversine formula to calculate the great-circle distance between two places on a sphere. The formula is given by $d_{12} = R \times 2 \times \arcsin \left( \min(1, \sqrt{h}) \right)$, where $R$ is the earth’s radius (approximately 6371 km), $h = \left( \sin \left( \frac{\Delta \text{lat}}{2} \right) \right)^2 + \cos \left( \text{lat}_1 \right) \times \cos \left( \text{lat}_2 \right) \times \left( \sin \left( \frac{\Delta \text{long}}{2} \right) \right)^2$, $\Delta \text{lat} = \text{lat}_1 - \text{lat}_2$, $\Delta \text{long} = \text{long}_1 - \text{long}_2$, and lati and longi are the latitude and longitude of a county, respectively.
results in Model 3 show similar pattern of an insignificant effect of EWEs at the four closest neighboring counties on climate ratings. If headquarter county captures the principal residing locale of managers, the results in Table I7 demonstrate that personal rather than possibly vicarious experiences of EWEs is of paramount importance to determine climate ratings.

It is notable that the insignificant effects of the EWEs at the neighboring counties on climate ratings seem in spirit to be inconsistent with the results in Dessaint and Matray (2017), who show that managers residing at a region which is in the neighborhood of the hurricane areas nonetheless overact to the hurricane risk by holding excessive amount of cash. Though sorting out the reasons to fully explain the difference in results is beyond the scope of this paper, I note three possible explanations. First, unlike the liquidity decision that relates to daily operations, the decision on climate policies seems less urgent from a firm’s perspective. As a result, the hurdle above which managers are motivated to act may be higher for the latter type of decisions, and hence personal experiencing of EWEs may be indispensable to overcome this hurdle. Second, the results in Table 4 in the main text suggest that flooding is the most prominent type of EWEs to impact climate ratings. The statistics further show that most of the flood events is flash flood, which tends to be locally incurred. As a result, if these flood events are not reported by the media and if no one in the flood area describes these experiences to a manager, he/she may well be unaware of these events at all. Finally, though the EWEs in this study may be intense enough to alter managerial belief in ACC and hence change corporate climate policies, the intensity of these disasters may still not be comparable to hurricanes. Therefore, the same logic as in the first explanation applies – while managers may act to the risk of hurricanes by simply observing their impact on neighbors, personal experiencing the types of EWEs as in this study may be indispensable for them to overcome the hurdle to take actions.
10. Corporate Governance and Effect of EWEs on Climate Ratings

Though I have argued that experiencing EWEs by managers is likely to change or enhance their beliefs in ACC and motivate them to adopt friendlier corporate mitigation policies, a positive and significant relation between the EWEs in the headquarter of a firm and its climate rating leaves space for alternative explanations of the result. To provide more direct evidence for the role managers may play in this relation, I examine whether the governance mechanisms of a firm may shape this relation. The rationale is that managers should have more leeway to imprint their personal beliefs on corporate policies if they are more powerful hence the governance of the firm is weaker (Cronqvist, Makhija, & Yonker, 2012). I consider three types of governance mechanisms, CEO tenure, board size, and antitakeover mechanisms. I obtain the data for these governance mechanisms from the Institutional Shareholder Service (formerly RiskMetrics) Director and Antitakeover databases, which cover the director profiles and antitakeover devices of the S&P 1,500 firms. First, longer tenure may indicate managerial power and entrenchment (Hermalin & Weisbach, 1998). An entrenched CEO should have a stronger influence on corporate decision-making. In Model 1 of Table I8, I interact EWE with a Longer tenure dummy, which equals one if the tenure of a CEO is longer than the sample median, and zero otherwise. I expect the interaction term to be positive and significant. The results show that although it is positive, it is not significant. Second, because of the coordination difficulty and free-rider problem, larger boards are generally associated with weaker governance (Eisenberg, Sundgren, & Wells, 1998; Yermack, 1996). Therefore, in Model 2 of Table I8 I interact EWE with a Larger board dummy, which equals one if the board size is larger than the sample median, and zero otherwise. As predicted, the interaction term EWE * Larger board is positive and significant. Third, firms with more antitakeover mechanisms in place are generally associated with a lower valuation because of
the presumably stronger protection against external market discipline as afforded by these devices (L. Bebchuk, Cohen, & Farrell, 2009; Gompers, Ishii, & Metrick, 2003). L. A. Bebchuk and Cohen (2005) further show that among the 24 major antitakeover mechanisms (the components of the G-index as in Gompers et al. (2003)), classified board is the most critical. Therefore, in Model 3 of Table I8 I interact EWE with a Classified board dummy, which equals one if the election of the board of directors of a firm is staggered, and zero otherwise.\textsuperscript{17} The results show that the interaction term is positive but not significant.

Altogether, the results in Table I8 provide some evidence that is consistent with the argument that stronger managerial power as afforded by weaker corporate governance makes it easier for managers to imprint their personal beliefs in ACC on corporate climate mitigation policies after experiencing EWEs. However, these results still cannot rule out the possibility that local stakeholders of the firm, after witnessing EWEs or suffering great losses from them, push managers to adopt friendlier climate policies. For example, the stronger effect of EWEs on climate ratings under a larger board may be driven by the increased chance of connecting with some board members hence shaping corporate policies by local stakeholders because of the simple fact that the board has more members. At the minimum, however, these results suggest that managers do play a role in the relation between EWEs in their headquarters and climate ratings.

11. Damage Hypothesis

One alternative explanation for the significantly positive effect of EWEs on climate ratings is that in response to the damages caused by EWEs to a firm’s properties at the headquarter, the firm replaces the assets with presumably more energy-efficient ones, hence earning a climate strength

\textsuperscript{17} Another reason for me to use classified board instead of the G-index (or a refined E-index as in L. Bebchuk et al. (2009)) is that some components that are needed to calculate the G-index or the E-index are not available after 2006.
rating. In addition to the arguments made in the main text, I conduct two additional tests in this section to further examine this “Damage Hypothesis”.

First, note that the arguments made in the previous section suggest that many of the EWEs used in the construction of the primary EWE variable tend to be local, such as flash flood. Actually, I find that the correlation between the EWEs at the headquarter county and those of the closest neighboring county is only 0.41. Though still high, this statistic is nonetheless more consistent with the “local EWEs” argument above. If this is the case, and since the firms in my sample are the largest public firms in the U.S., it may be reasonable to expect that the psychological impact of the EWEs incurred at the headquarters of these firms is more significant than their economic impact. Though I lack the data on the geographic distribution of these firms’ assets to better test this argument, it might be reasonable to expect that the larger a firm is, the less economically important are the physical assets at the firm’s headquarter since they are expected to be a smaller fraction of the firm’s total assets. If this is the case, then the Damage Hypothesis should be more applicable to smaller firms with fewer assets, because then the assets at their headquarters may be more significant. Therefore, in Model 1 of Table I9, I interact EWE with a Small size dummy, which equals one if the lagged value of the total asset of a firm is at or below the sample median, and zero otherwise. If Damage Hypothesis holds, I expect this interaction term to be positive and significant. However, as shown the interaction term is negative and insignificant.

Between the two major types of assets, tangible and intangible, tangible assets should be subject more to the arguments in the Damage Hypothesis, hence firms with more tangible assets/higher capital intensity should be a better candidate to be consistent with this hypothesis. Therefore, in Model 2 I interact EWE with a High capital intensity dummy, which equals one if the lagged value of the capital intensity (gross PPE divided by total assets) of a firm is above the sample median,
and zero otherwise. The Damage Hypothesis would predict a positive and significant interaction term. But the results in Model 2 show that it is not significant.

Finally, since energy efficiency tends to improve over time with technological progress, new assets are likely to improve more significantly in terms of carbon footprint if replacing older assets, which may result in a climate strength rating. Therefore, firms with older tangible assets are more likely to earn a strength rating when incurring EWEs if the Damage Hypothesis holds. To examine this possibility, in Model 3 I interact EWE with an Old PPE dummy that equals one if the industry-adjusted lagged percent used-up of PPE (accumulated depreciation/gross PPE) is above the sample median, and zero otherwise. The indicator variable for the age of the tangible assets – percent used-up of PPE is adjusted for the industry average to consider the different nature of assets in different industries, which may result in different expected life of the assets. Though the Damage Hypothesis predicts a positive interaction term, the result in Model 3 is negative and insignificant.

12. Changing Extreme Weather Type and Climate Ratings

One prediction of the theory based on the two fundamental information processing systems and the attention-based view of the firm as discussed in the main text is that the occurrence of a new type of EWE may have a more pronounced impact on climate ratings as compared to merely more frequent incidences of EWEs of the same types. The fundamental reason for this is that both theories are based on direct experiences of climate stimuli, and a different kind of EWE experiences may more easily generate awareness and/or a change in belief in ACC. A rigorous examination of this hypothesis requires an identification of the “normal” type(s) of EWE(s) at a specific location. However, the Storm database that I employ for EWEs does not allow for a strict identification of the “normal” EWE(s). The reason for this is because the database starts in 1996 and my sample starts in 1997 (because I use the lagged values of EWEs), so there is no historical
information to identify the trend of EWEs which might more plausibly serve as the “normal” EWEs at a location. Despite this difficulty, I use two methods to roughly identify the “normal” EWE(s) to examine the plausibility of this Changing Type Hypothesis (CTH). The results are presented in Table I10.

In Model 1, I take the EWE(s) that first appeared in a given headquarter county in the previous year during my sample period as the normal EWE(s), where the EWEs are grouped into the four categories as in Appendix B of the main text. I then create a dummy variable that equals one if in the previous year a new category of EWEs first appeared in the county, and zero otherwise. The CTH would predict a positive interaction of this dummy with EWE. Indeed, the results in Model 1 are consistent with this prediction. The identification of normal EWE(s) in Model 2 is similar, except that the set of EWEs in consideration for normal EWE(s) is not limited to those four categories of EWEs as in Model 1, but the EWEs in the definition of the EWE1 variable in Model 2 of Table I3. This enlargement of the set of EWEs to identify normal EWE(s) does not change the results. The interaction term is still positive and highly significant.

One obvious drawback of using the earliest EWE(s) during the sample period to identify normal EWE(s) as in these two models is that since there is no historical trend, the first appearance in the sample does not necessarily suggest this (these) EWE(s) is (are) the most common type(s) of EWE(s) in the county. Model 3 attempts to alleviate this concern. Specifically, instead of using historical trend, I define the category (categories) of EWEs as in Appendix B of the main text to be normal for a headquarter county if it (they) appears (appear) most often in the sense that it (they) occurred in the county for the largest number of years between 1997 and 2019. I extend the sample to the year 2019 to more accurately identify the trend. In the event of ties, I identify the normal EWE(s) as that (those) occurred for the largest number of times between 1997 and 2019. In a sense,
this way of identifying the normal EWE(s) assumes that the historical trend continues. Given the nature of climate change, the plausibility of this assumption is questionable. Despite this drawback, the results in Model 3 of Table I10 provide further support for the CTH in that the interaction term with respect to the dummy indicating the appearance of a new category of EWE and EWE is positive, albeit only weakly significant at the 10% level. Finally and similar to Model 2, Model 4 expands the set of EWEs in consideration for normal EWE(s) to be those in the definition of EWE1, but the results are similar.

Collectively, the results in Table I10 suggest the plausibility of the CTH despite the drawbacks as discussed above in identifying the normal type(s) of EWE(s) at a given location.
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**Figure II. Time Trend of Climate Strength**
This figure shows the time trend of climate strength, which suggests the change in the definitions of this variable over time. The dot in the figure represents the annual cross-sectional average of this variable.
Table I1. Definitions of Climate Change Related Policy Ratings in KLD

| Variable           | Time Period                        | Definition                                                                                                                                                                                                 |
|--------------------|-----------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Climate strength   | Before 2010 (named “Clean Energy”) | The company 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. The company has demonstrated a commitment to promoting climate-friendly policies and practices outside its own operations. |
|                    | On or after 2010                   | This indicator measures a firm’s policies, programs, and initiatives regarding climate change. Factors affecting this evaluation include, but are not limited to, the following:                                     |
|                    |                                   | • Companies that invest in renewable power generation and related services.                                                                                                                                   |
|                    |                                   | • Companies that invest in efforts to reduce carbon exposure through comprehensive carbon policies and implementation mechanisms, including carbon reduction objectives, production process improvements, installation of emissions capture equipment, and/or switch to cleaner energy sources. |
|                    |                                   | • Companies that take proactive steps to manage and improve the energy efficiency of their operations.                                                                                                      |
|                    |                                   | • Companies that measure and reduce the carbon emissions of their products throughout the value chain and implement programs with their suppliers to reduce carbon footprint.                                 |
|                    |                                   | • Insurance companies that have integrated climate change effects into their actuarial models while developing products to help customers manage climate change related risks.                                |
| Climate concern    | Before 2012                        | The company 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. |
|                    | On or after 2012                   | This indicator measures the severity of controversies related to a firm’s climate change and energy-related policies and initiatives. Factors affecting this evaluation include, but are not limited to, a history of involvement in GHG-related legal cases, widespread or egregious impacts due to corporate GHG emissions, resistance to improved practices, and criticism by NGOs and/or other third-party observers. |
Table I2. Alternative Samples

This table reports the robustness of the results by using alternative samples. Sample 1 is the full sample without excluding any industries/firms. Sample 2 excludes all the industries with “NR” (not rated) markings by MSCI at 2012. Sample 3 excludes all the industries with “consistent” “NR” markings by MSCI at 2012, where consistency is defined as the situation when all the firms in the same industry are marked as “NR”. Sample 4 excludes all the industries with consistent “NR” markings by MSCI at 2012 and consistent “0” Climate rating between 1997 and 2009. Sample 5 includes the S&P 500 firms at 2006 with the headquarter county data manually collected for the sample period. The dependent variable for each model is Climate rating. See Appendix A in the main text for the definitions of all the 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.

| Sample                               | (1) | (2) | (3) | (4) | (5) |
|--------------------------------------|-----|-----|-----|-----|-----|
|                                      | EWE | Net CER | Net CSR | Size | S&P 500 at 2006 |
|                                      |     | Full | Exclude industries with any “NR” at 2012 | Exclude industries with consistent “NR” at 2012 | Exclude industries with consistent “0” Climate rating between 1997 and 2009 | with historical headquarter county data |
|                                      |     |     |     |     |     |     |
|                                      | 0.007*** | 0.158*** | 0.033*** | 0.024*** | 0.032* |
|                                      | (3.817) | (2.846) | (3.092) | (7.639) | (1.944) |
| Net CER                              | 0.010** | 0.145** | 0.031* | 0.034*** | 0.145** |
|                                      | (2.467) | (2.224) | (1.938) | (6.127) | (2.467) |
| EWE                                  | 0.158*** | 0.158*** | 0.033*** | 0.024*** | 0.035* |
|                                      | (3.774) | (2.845) | (3.105) | (7.559) | (2.847) |
| Size                                 | 0.007*** | 0.007*** | 0.007*** | 0.007*** | 0.007*** |
|                                      | (3.812) | (2.847) | (3.105) | (7.653) | (1.885) |
| ROA                                  | -0.001 | -0.022 | -0.000 | -0.001 | -0.061 |
|                                      | (-0.079) | (-1.103) | (-0.015) | (-0.075) | (-1.195) |
| Net CSR                              | -0.023 | -0.036** | -0.038** | -0.001 | -0.061 |
|                                      | (-2.306) | (-2.202) | (-2.287) | (-0.075) | (-1.121) |
| Salesgrow                            | -0.037*** | -0.094*** | -0.037*** | 0.035* | 0.035* |
|                                      | (-2.788) | (-2.939) | (-2.758) | (1.039) | (1.039) |
| ROA                                  | 0.023 | 0.033** | 0.033** | 0.033** | 0.289* |
|                                      | (2.519) | (2.495) | (2.509) | (2.758) | (1.674) |
| Capexp                               | 0.131 | 0.245*** | 0.247*** | 0.767* | 0.767* |
|                                      | (2.787) | (2.777) | (2.796) | (2.796) | (1.809) |
| Dividend                             | 0.023 | 0.033** | 0.033** | 0.033** | 0.289* |
|                                      | (0.906) | (2.495) | (2.509) | (2.758) | (1.674) |
| Capexp                               | 0.246*** | 0.131 | 0.245*** | 0.035* | 0.767* |
|                                      | (2.787) | (1.163) | (2.777) | (1.039) | (1.039) |
| R&D                                  | -0.037*** | -0.094*** | -0.037*** | 0.035* | 0.035* |
|                                      | (-2.788) | (-2.939) | (-2.758) | (1.039) | (1.039) |
| Adver                                | 0.023 | 0.033** | 0.033** | 0.033** | 0.289* |
|                                      | (0.434) | (0.827) | (0.984) | (0.378) | (0.378) |
| Cash                                 | 0.011 | 0.007 | 0.010 | 0.011 | -0.064 |
|                                      | (0.864) | (0.226) | (0.734) | (0.839) | (-0.479) |
| Observations                         | 17,349 | 7,193 | 17,276 | 17,297 | 2,160 |
| Adjusted R²                           | 0.35 | 0.35 | 0.35 | 0.35 | 0.46 |

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Table I3. Alternative Measures of EWEs

This table reports the robustness of the results by using alternative measures of EWEs. EWE (no drought) is the EWE variable excluding drought. EWE1 is the lagged sum of the annual number of extreme weather events as listed in Table I4. 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. EWEt is the contemporaneous value of EWE. See Appendix A in the main text for the definitions of all other variables. The dependent variable for each model is Climate rating. The control variables for Model 6/the other models are at their contemporaneous/one-year lagged values. All models also include 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 for all the models except for Model 5, and at both the firm and state-year levels for Model 5. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

|                           | (1)      | (2)      | (3)      | (4)      | (5)      | (6)      |
|---------------------------|----------|----------|----------|----------|----------|----------|
| EWE (no drought)          | 0.013*** |          |          |          |          |          |
|                           | (3.761)  |          |          |          |          |          |
| EWE1                      | 0.022*** |          |          |          |          |          |
|                           | (4.156)  |          |          |          |          |          |
| Cold event                | 0.003*   | 0.006*** |          |          |          |          |
|                           |          | (1.770)  |          |          |          |          |
| Cold/Wind chill           |          | -0.001   |          |          |          |          |
|                           |          | (-0.382) |          |          |          |          |
| Extreme cold/Wind chill   |          | -0.002** |          |          |          |          |
|                           |          | (-2.519) |          |          |          |          |
| Frost/Freeze              |          |          | 0.003**  |          |          |          |
|                           |          |          | (2.138)  |          |          |          |
| Billion disaster loss     |          |          |          | 0.006*   |          |          |
|                           |          |          |          | (1.874)  |          |          |
| EWEt                      |          |          | 0.002*** | 0.002*** | 0.002*** | 0.002*** |
|                           |          |          | (2.989)  | (3.094)  | (2.989)  | (3.094)  |
| Net CER                   | 0.158**  | 0.158**  | 0.158**  | 0.159**  | 0.158**  | 0.154**  |
|                           | (2.259)  | (2.259)  | (2.258)  | (2.265)  | (2.458)  | (2.454)  |
| Net CSR                   | 0.060*** | 0.060*** | 0.060*** | 0.060*** | 0.056*** | 0.055*** |
|                           | (3.189)  | (3.173)  | (3.194)  | (3.200)  | (3.151)  | (3.132)  |
| Size                      | 0.040*** | 0.040*** | 0.040*** | 0.040*** | 0.047*** | 0.035*** |
|                           | (6.955)  | (6.952)  | (6.950)  | (6.955)  | (7.972)  | (7.311)  |
| Salesgrow                 | 0.003    | 0.003    | 0.003    | 0.002    | 0.008    | 0.015    |
|                           | (0.229)  | (0.207)  | (0.219)  | (0.192)  | (0.582)  | (1.543)  |
| ROA                       | -0.114***| -0.113***| -0.113***| -0.113***| -0.123***| -0.094***|
|                           | (-3.879) | (-3.852) | (-3.873) | (-3.851) | (-4.046) | (-4.407) |
| Leverage                  | -0.086***| -0.085***| -0.086***| -0.085***| -0.077***| -0.056***|
|                           | (-3.306) | (-3.276) | (-3.301) | (-3.273) | (-2.859) | (-2.687) |
| Dividend                  | 0.101*** | 0.101*** | 0.101*** | 0.100*** | 0.073*** | 0.082*** |
|                           | (2.824)  | (2.837)  | (2.824)  | (2.803)  | (2.062)  | (2.880)  |
| Capexp                    | 0.373**  | 0.373**  | 0.373**  | 0.373**  | 0.411*** | 0.336*** |
|                           | (2.569)  | (2.570)  | (2.573)  | (2.571)  | (2.918)  | (2.831)  |
| R&D                       | -0.120   | -0.118   | -0.119   | -0.119   | -0.029   | -0.089   |
|                           | (-1.594) | (-1.571) | (-1.586) | (-1.578) | (-0.388) | (-1.486) |
| Adver                     | 0.163    | 0.169    | 0.162    | 0.157    | 0.249    | 0.094    |
|                           | (0.707)  | (0.735)  | (0.701)  | (0.682)  | (1.091)  | (0.497)  |
| Cash                      | 0.047*   | 0.046*   | 0.046*   | 0.046*   | 0.086*** | 0.052**  |
|                           | (1.670)  | (1.651)  | (1.657)  | (1.655)  | (3.196)  | (2.284)  |

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| Observations    | 7,706 | 7,706 | 7,706 | 7,706 | 7,730 | 9,481 |
|-----------------|-------|-------|-------|-------|-------|-------|
| State FE        | No    | No    | No    | No    | Yes   | No    |
| County FE       | Yes   | Yes   | Yes   | Yes   | No    | Yes   |
| Adjusted R²     | 0.40  | 0.40  | 0.40  | 0.40  | 0.33  | 0.42  |

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| Event Type               | Used in EWE1 Definition? | Event Type               | Used in EWE1 Definition? |
|-------------------------|--------------------------|-------------------------|--------------------------|
| Astronomical Low Tide   | No                       | High Wind               | Yes                      |
| Avalanche               | No                       | Hurricane (Typhoon)     | Yes                      |
| Blizzard                | Yes                      | Ice Storm               | Yes                      |
| Coastal Flood           | Yes                      | Lake-Effect Snow        | Yes                      |
| Cold/Wind Chill         | No                       | Landslide               | No                       |
| Debris Flow             | No                       | Lightning               | Yes                      |
| Dense Fog               | No                       | Northern Lights         | No                       |
| Dense Smoke             | No                       | Rip Current             | No                       |
| Drought                 | Yes                      | Seiche                  | No                       |
| Dust Devil              | No                       | Sleet                   | Yes                      |
| Dust Storm              | No                       | Storm Surge/Tide        | Yes                      |
| Excessive Heat          | Yes                      | Strong Wind             | Yes                      |
| Extreme Cold/Wind Chill| No                       | Thunderstorm Wind       | Yes                      |
| Flash Flood             | Yes                      | Tornado                 | Yes                      |
| Flood                   | Yes                      | Tropical Depression     | Yes                      |
| Frost/Freeze            | No                       | Tropical Storm          | Yes                      |
| Funnel Cloud            | No                       | Tsunami                 | No                       |
| Freezing Fog            | No                       | Volcanic Ash            | No                       |
| Hail                    | Yes                      | Waterspout              | No                       |
| Heat                    | Yes                      | Wildfire                | Yes                      |
| Heavy Rain              | Yes                      | Winter Storm            | Yes                      |
| Heavy Snow              | Yes                      | Winter Weather          | Yes                      |
| High Surf               | Yes                      | Other                   | No                       |
Table 15. More Robustness Tests

This table reports more results to check the robustness of the relationship between EWEs and climate ratings. Ind norm net CER/CSR is the net environmental/social score (total strength count – total concern count) minus the minimum value of this score in the firm’s industry, scaled by the industry range (maximum – minimum) of this score in the previous year. The dependent variable for each model is Climate rating. See Appendix A in the main text for the definitions of all other variables. Models 1 & 3 also include the county FEs and the interactions of year and three-digit SIC industry FEs. Model 2 also includes the county and year 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.

| Model          | (1)       | (2)       | (3)       |
|----------------|-----------|-----------|-----------|
|                | Linear    | Probit    | Linear    |
| EWE            | 0.013***  | 0.142***  | 0.014***  |
|                | (2.951)   | (2.718)   | (2.709)   |
| Ind norm net CER | 0.032     |           |           |
|                | (1.129)   |           |           |
| Ind norm net CSR | 0.124***  |           |           |
|                | (4.353)   |           |           |
| Net CER        | -0.250    | 0.143*    | 0.138***  |
|                | (-0.798)  | (1.704)   | (1.388)   |
| Net CSR        | 0.454***  | 0.071***  |           |
|                | (3.996)   | (3.492)   |           |
| Size           | 0.036***  | 0.253***  | -0.038**  |
|                | (6.121)   | (6.440)   | (-2.265)  |
| Salesgrow      | -0.002    | 0.032     | 0.013     |
|                | (-0.180)  | (0.225)   | (0.922)   |
| ROA            | -0.115*** | -0.755    | 0.012     |
|                | (-3.760)  | (-1.559)  | (0.405)   |
| Leverage       | -0.084*** | 0.348     | -0.048    |
|                | (-3.086)  | (1.109)   | (-1.388)  |
| Dividend       | 0.113***  | 1.794***  | 0.051     |
|                | (2.822)   | (6.234)   | (1.495)   |
| Capexp         | 0.427***  | 3.414***  | 0.085     |
|                | (2.719)   | (4.072)   | (0.662)   |
| R&D            | -0.132*   | -3.668*** | -0.144    |
|                | (-1.722)  | (-2.705)  | (-1.599)  |
| Adver          | 0.273     | -6.828**  | -0.834    |
|                | (1.012)   | (-2.370)  | (-1.407)  |
| Cash           | 0.041     | -0.597    | 0.013     |
|                | (1.451)   | (-1.337)  | (0.366)   |
| Observations   | 6.900     | 7.706     | 7.463     |
| Firm FE        | No        | No        | Yes       |
| Adjusted R²    | 0.41      |           | 0.62      |
| Pseudo R²      |           | 0.28      |           |

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Table I6. Alternative Industry Classifications  
This table reports the robustness of the results by alternative industry classifications. SIC4, SIC2, FF48, and FF12 is the industry classified by four-digit SIC code, two-digit SIC code, Fama-French 48 industries, and Fama-French 12 industries, respectively. The dependent variable for each model is Climate rating. See Appendix A in the main text for the definitions of all the variables. All models also include the county FEs and the interactions of year and corresponding 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.

| EWE       | 0.011** | 0.011** | 0.012** | 0.011** |
|-----------|---------|---------|---------|---------|
|           | (2.532) | (2.455) | (2.488) | (2.347) |
| Net CER   | 0.153** | 0.149** | 0.155** | 0.145** |
|           | (2.047) | (2.180) | (2.211) | (2.142) |
| Net CSR   | 0.061*** | 0.061*** | 0.062*** | 0.061*** |
|           | (3.229) | (3.433) | (3.382) | (3.473) |
| Size      | 0.039*** | 0.036*** | 0.038*** | 0.035*** |
|           | (6.507) | (6.495) | (6.815) | (6.845) |
| Salesgrow | 0.004   | -0.007  | -0.008  | -0.007  |
|           | (0.295) | (-0.595) | (-0.656) | (-0.536) |
| ROA       | -0.127*** | -0.111*** | -0.100*** | -0.098*** |
|           | (-4.046) | (-3.493) | (-3.380) | (-3.219) |
| Leverage  | -0.095*** | -0.076*** | -0.071*** | -0.055*** |
|           | (-3.533) | (-2.921) | (-2.798) | (-2.271) |
| Dividend  | 0.098*** | 0.089*** | 0.086*** | 0.098*** |
|           | (2.631) | (2.584) | (2.404) | (2.844) |
| Capexp    | 0.411*** | 0.519*** | 0.467*** | 0.414*** |
|           | (2.777) | (3.688) | (3.270) | (3.128) |
| R&D       | -0.111   | -0.177** | -0.117  | -0.049  |
|           | (-1.368) | (-2.383) | (-1.608) | (-0.709) |
| Adver     | 0.088   | 0.233   | 0.146   | 0.184   |
|           | (0.315) | (1.033) | (0.605) | (0.801) |
| Cash      | 0.037   | 0.025   | 0.034   | 0.029   |
|           | (1.334) | (0.899) | (1.263) | (1.186) |
| Observations | 7,440   | 7,706   | 7,675   | 7,705   |
| Industry Classification | SIC4 | SIC2 | FF48 | FF12 |
| Adjusted R² | 0.41 | 0.35 | 0.35 | 0.35 |
Table 17. Extreme Weather at Neighboring Counties and Climate Ratings

This table examines the effect of EWEs at neighboring counties on climate ratings. EWE_{nb,x,y} is the average of the annual numbers of EWEs incurred at the counties which lie between x and y kilometers of the headquarter county of the firm. EWE_{nb,i} is the number of EWEs of the i-th closest county to the headquarter county of the firm. The dependent variable for each model is Climate rating. See Appendix A in the main text 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)            | (3)            |
|----------------|----------------|----------------|----------------|
| EWE            | 0.014***       | 0.017**        | 0.013**        |
|                | (2.707)        | (2.469)        | (2.575)        |
| EWE_{nb0-200}  | -0.001         | (-0.266)       |                |
|                |                |                | (-0.664)       |
| EWE_{nb0-100}  | -0.006         | (-0.856)       |                |
| EWE_{nb100-200}|                | 0.002          |                |
|                |                | (0.371)        |                |
| EWE_{nb200-300}|                | 0.002          |                |
|                |                | (0.825)        |                |
| EWE_{nb300-400}|                | -0.004         |                |
|                |                | (-0.723)       |                |
| EWE_{nb1}      |                |                | -0.000         |
|                |                |                | (-0.086)       |
| EWE_{nb2}      |                |                | 0.002          |
|                |                |                | (0.442)        |
| EWE_{nb3}      |                |                | -0.001         |
|                |                |                | (-0.131)       |
| EWE_{nb4}      |                |                | -0.003         |
|                |                |                | (-0.672)       |
| Net CER        | 0.158**        | 0.156**        | 0.158**        |
|                | (2.257)        | (2.229)        | (2.258)        |
| Net CSR        | 0.060***       | 0.060***       | 0.060***       |
|                | (3.194)        | (3.178)        | (3.198)        |
| Size           | 0.040***       | 0.040***       | 0.040***       |
|                | (6.946)        | (6.932)        | (6.949)        |
| Salesgrow      | 0.003          | 0.003          | 0.003          |
|                | (0.220)        | (0.214)        | (0.215)        |
| ROA            | -0.114***      | -0.111***      | -0.114***      |
|                | (-3.883)       | (-3.670)       | (-3.866)       |
| Leverage       | -0.086***      | -0.083***      | -0.086***      |
|                | (-3.300)       | (-3.082)       | (-3.300)       |
| Dividend       | 0.101***       | 0.106***       | 0.101***       |
|                | (2.831)        | (2.904)        | (2.831)        |
| Capexp         | 0.373**        | 0.396***       | 0.373**        |
|                | (2.572)        | (2.659)        | (2.572)        |
| R&D            | -0.120         | -0.122         | -0.120         |
|                | (-1.599)       | (-1.522)       | (-1.594)       |
| Adver          | 0.164          | 0.137          | 0.161          |
|                | (0.710)        | (0.575)        | (0.699)        |
| Cash           | 0.046*         | 0.049*         | 0.046*         |
|                | (1.663)        | (1.696)        | (1.663)        |
| Observations   | 7,706          | 7,520          | 7,706          |
| Adjusted $R^2$ | 0.40 | 0.40 | 0.40 | 0.40 |
Table I8. Extreme Weather, Corporate Governance, and Climate Ratings
This table examines the impact of governance mechanisms on the effect of EWEs on climate ratings. Longer tenure is a dummy variable that equals one if the tenure of the CEO is longer than the median value in the sample, and zero otherwise. Larger board is a dummy variable that equals one if the board size is larger than the median value in the sample, and zero otherwise. Classified board is a dummy variable that equals one if the election of the board of directors of a firm is classified, and zero otherwise. The dependent variable for each model is Climate rating. See Appendix A in the main text 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)         | (3)         |
|--------------------------|-------------|-------------|-------------|
| EWE                      | 0.017**     | 0.005       | 0.016*      |
|                          | (2.229)     | (0.803)     | (1.711)     |
| EWE * Longer tenure      | 0.002       |             |             |
|                          | (0.211)     |             |             |
| Longer tenure            | -0.003      |             |             |
|                          | (-0.192)    |             |             |
| EWE * Larger board       |             | 0.029**     |             |
|                          |             | (2.217)     |             |
| Larger board             | 0.019       |             |             |
|                          | (1.254)     |             |             |
| EWE * Classified board   |             |             | 0.001       |
|                          |             |             | (0.109)     |
| Classified board         | 0.001       |             |             |
|                          | (0.074)     |             |             |
| Net CER                  | 0.204***    | 0.179**     | 0.159**     |
|                          | (2.613)     | (2.419)     | (2.195)     |
| Net CSR                  | 0.077***    | 0.075***    | 0.072***    |
|                          | (3.360)     | (3.365)     | (3.455)     |
| Size                     | 0.055***    | 0.048***    | 0.049***    |
|                          | (6.812)     | (5.721)     | (6.493)     |
| Salesgrow                | -0.033      | -0.034      | -0.031      |
|                          | (-1.285)    | (-1.395)    | (-1.519)    |
| ROA                      | -0.050      | -0.049      | -0.075*     |
|                          | (-1.071)    | (-1.065)    | (-1.745)    |
| Leverage                 | -0.058      | -0.063      | -0.060*     |
|                          | (-1.299)    | (-1.444)    | (-1.654)    |
| Dividend                 | 0.152***    | 0.145***    | 0.137***    |
|                          | (2.651)     | (2.601)     | (2.625)     |
| Capexp                   | 0.289       | 0.291       | 0.317*      |
|                          | (1.492)     | (1.561)     | (1.755)     |
| R&D                      | -0.214*     | -0.211*     | -0.114      |
|                          | (-1.653)    | (-1.662)    | (-1.014)    |
| Adver                    | 0.350       | 0.285       | 0.179       |
|                          | (1.077)     | (0.904)     | (0.577)     |
| Cash                     | 0.017       | 0.006       | 0.033       |
|                          | (0.385)     | (0.134)     | (0.822)     |
| Observations             | 4,944       | 5,246       | 5,618       |
| Adjusted R²              | 0.44        | 0.45        | 0.44        |
Table I9. Testing the Damage Hypothesis

This table examines the Damage Hypothesis, which states that the positive and significant impact of EWEs on climate ratings is driven by firms’ replacing their damaged assets from the EWEs with new and less carbon-intensive ones. Small size is a dummy variable that equals one if the lagged total assets of the firm is at or below the sample median, and zero otherwise. High capital intensity is a dummy variable that equals one if the lagged capital intensity (gross PPE scaled by total assets) of the firm is above the sample median, and zero otherwise. Old PPE is a dummy variable that equals one if the lagged industry-adjusted percent used-up of PPE (accumulated depreciation/gross PPE) of the firm is above the sample median, and zero otherwise. The dependent variable for each model is Climate rating. See Appendix A in the main text 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)       | (3)       |
|--------------|-----------|-----------|-----------|
| EWE          | 0.019**   | 0.011*    | 0.009*    |
|              | (2.252)   | (1.914)   | (1.885)   |
| EWE * Small size | -0.012    |            |           |
|              | (-1.112)  |           |           |
| Small size   | -0.001    |           |           |
|              | (-0.102)  |           |           |
| EWE * High capital intensity | 0.003    |            |           |
|              | (0.295)   |           |           |
| High capital intensity | -0.007    |            |           |
|              | (-0.493)  |           |           |
| EWE * Old PPE |          | -0.005    |           |
|              |           | (-0.656)  |           |
| Old PPE      | 0.003     |           |           |
|              | (0.405)   |           |           |
| Net CER      | 0.158**   | 0.163**   | 0.183**   |
|              | (2.258)   | (2.311)   | (2.399)   |
| Net CSR      | 0.060***  | 0.063***  | 0.060***  |
|              | (3.208)   | (3.324)   | (3.180)   |
| Size         | 0.039***  | 0.040***  | 0.044***  |
|              | (5.784)   | (6.879)   | (7.802)   |
| Salesgrow    | 0.003     | 0.002     | 0.013     |
|              | (0.226)   | (0.149)   | (1.077)   |
| ROA          | -0.112*** | -0.114*** | -0.115*** |
|              | (-3.832)  | (-3.859)  | (-4.044)  |
| Leverage     | -0.085*** | -0.085*** | -0.050**  |
|              | (-3.271)  | (-3.239)  | (-2.081)  |
| Dividend     | 0.102***  | 0.114***  | 0.116***  |
|              | (2.833)   | (3.118)   | (3.224)   |
| Capexp       | 0.378***  | 0.395**   | 0.461***  |
|              | (2.600)   | (2.548)   | (3.339)   |
| R&D          | -0.120    | -0.114    | -0.126*   |
|              | (-1.586)  | (-1.512)  | (-1.718)  |
| Adver        | 0.152     | 0.146     | 0.117     |
|              | (0.658)   | (0.630)   | (0.520)   |
| Cash         | 0.045     | 0.043     | 0.075***  |
|              | (1.606)   | (1.569)   | (2.898)   |
| Observations | 7,691     | 7,590     | 6,808     |
| Adjusted R²  | 0.40      | 0.41      | 0.33      |
Table I10. Changing Extreme Weather Type and Climate Ratings

This table reports the results to examine the possibility that changing extreme weather type may have a more pronounced impact on climate ratings than simply having more frequent but the same type(s) of extreme weather event(s). New type based on time (1)/duration (1) is a dummy variable that equals one if in the previous year a new category of EWE among the four categories as listed in Appendix B of the main text occurred in the headquarter county of a firm and zero otherwise, where the “normal” type of EWE at the county is based on the categories (types) of EWE(s) out of those listed in Appendix B of the main text (Table I4) that first occurred in the county in the previous year during the sample period/incurred in the county in the previous year over the largest number of years between 1997 and 2019 and, in the event of ties, for the largest number of times between 1997 and 2019. The dependent variable for each model is Climate rating. See Appendix A in the main text for the definitions of all other variables. All models also include the county FEs and the interactions of year and corresponding 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)       | (3)       | (4)       |
|--------------------------|-----------|-----------|-----------|-----------|
| EWE                      | 0.011***  | 0.011***  | 0.011***  | 0.011***  |
|                          | (2.920)   | (2.925)   | (2.983)   | (2.938)   |
| EWE * New type based on time | 0.027*** | (3.015)   |           |           |
| New type based on time   | -0.003    |           | (-0.263)  |           |
| EWE * New type based on time1 | 0.027*** | (3.100)   |           |           |
| New type based on time1  | -0.004    |           | (-0.419)  |           |
| EWE * New type based on duration | 0.017*  |           | (1.829)   |           |
| New type based on duration | -0.009   |           | (-0.934)  |           |
| EWE * New type based on duration1 | 0.018** |           | (1.979)   |           |
| Net CER                  | 0.157**   | 0.157**   | 0.157**   | 0.157**   |
|                          | (2.243)   | (2.242)   | (2.241)   | (2.241)   |
| Net CSR                  | 0.060***  | 0.060***  | 0.060***  | 0.060***  |
|                          | (3.194)   | (3.194)   | (3.193)   | (3.195)   |
| Size                     | 0.039***  | 0.039***  | 0.039***  | 0.040***  |
|                          | (6.941)   | (6.939)   | (6.941)   | (6.943)   |
| Salesgrow                | 0.002     | 0.002     | 0.003     | 0.003     |
|                          | (0.185)   | (0.180)   | (0.204)   | (0.206)   |
| ROA                      | -0.114*** | -0.114*** | -0.114*** | -0.114*** |
|                          | (-3.889)  | (-3.891)  | (-3.892)  | (-3.894)  |
| Leverage                 | -0.086*** | -0.086*** | -0.086*** | -0.086*** |
|                          | (-3.294)  | (-3.298)  | (-3.302)  | (-3.297)  |
| Dividend                 | 0.102***  | 0.101***  | 0.101***  | 0.101***  |
|                          | (2.844)   | (2.842)   | (2.840)   | (2.838)   |
| Capexp                   | 0.373**   | 0.373**   | 0.374**   | 0.375***  |
|                          | (2.571)   | (2.570)   | (2.576)   | (2.580)   |
| R&D                      | -0.121    | -0.121    | -0.121    | -0.121    |
|                          | (-1.606)  | (-1.610)  | (-1.609)  | (-1.608)  |
| Adver                    | 0.160     | 0.160     | 0.160     | 0.161     |
|                          | (0.694)   | (0.696)   | (0.694)   | (0.697)   |
| Cash                     | 0.047*    | 0.047*    | 0.047*    | 0.047*    |
|                          | (1.676)   | (1.678)   | (1.676)   | (1.678)   |

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| Observations | 7,706 | 7,706 | 7,706 | 7,706 |
|--------------|-------|-------|-------|-------|
| Adjusted $R^2$ | 0.40  | 0.40  | 0.40  | 0.40  |