Natural Disasters and Corporate Climate Change Policies

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Abstract

Using county-level data on severe meteorological events in the United States, I show that controlling for fixed firm and county effects, the annual number of natural disasters sustained at a county significantly improve the rating of the climate change policies of a firm headquartered in that county. I examine three hypotheses that may explain this result. The evidence supports the hypothesis that experiencing natural disasters enhances beliefs in anthropogenic global warming and motivates managers to take climate-friendly actions. Finally, employing the instrumental variable method and a quasi-natural experiment, I show that climate ratings do not significantly affect firm performance.

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1. Introduction

Climate change is a recurring theme of our time. Despite the scientific consensus on the dominant role played by humans in global warming (GW) (Cook et al., 2013),[2] public and partisan beliefs in anthropogenic climate change (ACC) are divergent (Dunlap and McCright, 2008; Leiserowitz et al., 2017), resulting in a failure to enact federal legislations to limit greenhouse gas (GHG) emissions (Wallach, 2012).[3] It is then left to the individuals and firms to determine their own climate actions. Given the potentially catastrophic consequences of GW (IPCC, 2012b; Melillo et al., 2014; Stern, 2007; Weitzman, 2009), identifying the factors that shape beliefs in ACC, and whether these beliefs translate into concrete actions is important. While there is a large and growing literature in environmental psychology on the determinants of individual beliefs in ACC (e.g., Demski et al., 2017; Egan and Mullin, 2012; Konisky et al., 2016; Myers et al., 2013; Shao et al., 2014), no study to my knowledge analyzes the factors that determine managerial beliefs and whether these beliefs result in corporate climate change related policies (abbreviated as climate policy henceforth).[4] In this study, I fill the void and look at one possible such factor: experiencing of natural disasters. Specifically, I examine the relation between the annual number of severe meteorological events sustained at the headquarter counties of the largest publicly traded firms in the U.S. and the ratings of their climate policies (abbreviated as climate rating henceforth).

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

[3] There are only state and regional initiatives in the U.S. to combat ACC. California is the leader in enacting legislations to limit GHG emissions. Other states and regions that have taken actions include Arizona, Connecticut, Regional Greenhouse Gas Initiative which was a cap-and-trade program for CO_2 emissions formed by 9 Northeast states, Western Climate Initiative which was a GHG emissions trading system formed by 7 Western U.S. states and four Canadian provinces, and Powering the Plains Initiative by some Midwestern states and one Canadian province. But as discussed in Wallach (2012), these regional compacts suffer from collective action problems since states could exit the compacts without enforceable penalties. In contrast, a federal regulation could minimize this problem.

[4] There are two types of climate policies: climate mitigation, which is to reduce the severity of the potential effects of GW; and climate adaptation, which is to safeguard people and physical assets in a changed climate. I focus on the former in this paper.

The possible connection between extreme weather and climate policies is twofold. First, despite some uncertainties, the scientific models have pointed to an increase in the frequency and severity of some natural hazards due to ACC (IPCC, 2012b; Melillo et al., 2014).[5] Many hazards such as coastal sea rise, more frequent and/or severe incidences of hurricanes, droughts, flooding, excessive heat and wildfires have begun to manifest themselves in recent years (Gillis, 2016; IPCC, 2012b; Melillo et al., 2014). Second, experiencing natural disasters may be important for managers to update their beliefs in ACC and take climate actions, because most people rely on experiential learning in addition to analytical processing of information to form their beliefs (Marx et al., 2007). This may explain the disconnect between the scientific evidence requiring analytical digestion on one hand, and significant public disbelief in ACC on the other. Therefore, using severe meteorological events at a fine level of geographic resolution such as counties is crucial in my study, because it increases the likelihood that managers have indeed experienced these disasters.

The focus on the number of disasters rather than the economic damages caused by these disasters is due mostly to data limitations.[6] A legitimate concern is that some of the disasters may not be severe enough to affect beliefs. This concern is alleviated by the fact that the Storm Database from the National Oceanic and Atmospheric Administration (NOAA) in this study records only exceptional meteorological events with the "intensity to cause loss of life, injuries, significant property damage, and/or disruption to commerce" (NWS, 2016).[7] Compared with the number of

[5] However, the specific types of extreme weather that are expected to increase with ACC, and their spatial distributions and degrees of anthropogenic influence, are a topic of debate (Melillo et al., 2014). Heat waves, droughts, flooding, and wildfires are expected to rise with high statistical confidence. The frequency of other natural events and their human influences are more uncertain, including hurricanes, tornadoes, hail, thunderstorms, and winter storms. For robustness, I include different types of extreme weather in the definition of the disaster variable.

[6] Though I lack the insurance data for the economic damages of general disasters, I use the NOAA Billion-Dollar Disasters Database with estimated damages of the disasters causing at least $1 billion in inflation-adjusted losses for robustness checks, and obtain similar results. The results are presented in Table 9.

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

natural disasters, there are also downsides of using the insurance data on disaster losses, including its coarser geographic resolution, difficulty to accurately estimate economic damages, and risk to jeopardize the exogeneity of the disaster variable.[8]

Using a sample of the largest public companies in the U.S. from 1999 to 2012, an intersection of the NOAA Storm Database and MSCI ESG STATS (formerly KLD) Database on corporate social responsibility (CSR) ratings, I document a positive and significant impact of the annual number of natural disasters sustained at the headquarter county of a firm and its *subsequent* climate ratings. The results are robust to the inclusion of different types of weather events in the definition of the disaster variable. Importantly, I show that the result is significant only when controlling for fixed firm and especially county effects, suggesting that it is not the *level* of, but the *change* in disasters that matters for climate actions.[9] I also document an asymmetric impact of disasters on climate ratings conditional on the direction of the change in disasters: while an *increase* in disasters helps to *upgrade* a firm's climate rating, a *decrease* in disasters does not seem to *downgrade* it.[10]

Though a Belief Hypothesis (BH) that experiencing extreme weather enhances beliefs in ACC and motivates managers to take actions can explain these results and motivates this study, two

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[8] Most of the insurance data are at the state rather than a finer level of geographic resolution. In addition, estimating the economic damages associated with a natural hazard often has many practical complications. On one hand, since the purchase of insurance is voluntary, the data suffers from the selection problem. On the other hand, it is also challenging to adjust for factors such as demand surge and climate adaptation in such an estimate (e.g., Pielke Jr. et al., 2008; Simmons et al., 2013; Smith and Katz, 2013). These adjustments could well make the damage variable to be endogenous (Miao and Popp, 2014), hence jeopardizing one of the greatest advantages of studying the causal impact of natural disasters on climate policies.

[9] Another presumably more intuitive way to identify the relationship between the experiencing of a change in natural disasters and beliefs in ACC is by looking at the level of disasters relative to some long-term trend (Egan and Mullin, 2012). Unfortunately, in this study the Storm Database started the comprehensive coverage of the disasters only since 1996, leaving only two years (because disasters are lagged by one year) to identify the trend which is not practical. I note that one advantage of controlling for fixed effects rather than "de-trending" the disasters is that while the latter methodology still relies on cross-sectional variations of the variables other than disasters, the former depends on the time-variations of all the variables. In unreported analysis, I find that the first-difference regression results are similar to the results based on fixed-effects models.

[10] The changes here are all relative to their respective within county and firm average values over time. Unless causing confusions, these qualifications are omitted for space concerns.

alternative hypotheses are also plausible. In the Agency Cost Hypothesis (ACH), climate policies are an agency problem (Friedman, 1970), and as such management uses the possible connections between natural disasters and GW as an excuse to take climate actions to improve their reputation as good global citizens at the expense of shareholders (Barnea and Rubin, 2010; Cheng et al., 2016). On the other hand, the Regulatory Risk Hypothesis (RRH) states that managers choose climate-friendly policies because they expect possible regulations or litigations as a result of the substantial damages caused by disasters (Reid and Toffel, 2009). I conduct a battery of tests to examine these hypotheses. The evidence provides the strongest support for the BH.

Finally, using both the instrumental variable (IV) model and the election of Barack Obama, a strong advocate of ACC as the U.S. President as a quasi-natural experiment to exogenously increase climate actions, I show that climate ratings do not significantly affect firm performance.

This study attempts to make multiple contributions to the academic literature and policy debate on climate change. To my knowledge, this is the first study to analyze whether managerial belief in ACC matters for corporate climate actions, and the factors that may shape this belief. As such it adds to at least three areas of academic studies. First, a growing number of studies in environmental psychology also examine the relationship between experiencing natural disasters and survey takers' stated beliefs in ACC (e.g., Demski et al., 2017; Konisky et al., 2016; Myers et al., 2013). I distinguish from these studies in three fronts. First, unlike their focus on individuals and beliefs, I focus on professional managers and the eventual actions as a result of their beliefs - corporate climate policies. The distinction between beliefs and actions is important, since prior studies suggest that there can be significant distance between individuals' stated beliefs and their subsequent actions (GS Sustain, 2009; Kiron et al., 2013; PwC, 2015). Second, unlike these studies that document a cross-sectional relationship between the level of disasters and individual belief in

ACC, I show that managers seem to be more sophisticated and are mainly concerned about the *change in* disasters when updating their beliefs. Third, while earlier results typically find a transient effect of extreme weather on individual beliefs in ACC (e.g., Egan and Mullin, 2012; Konisky et al., 2016), I show that climate actions, though presumably harder to initiate in the first place, are also harder to reverse than beliefs.

I also add to the few studies that also analyze the determinants of the climate mitigation efforts of a firm (Aggarwal and Dow, 2012; Galbreath, 2010). These studies analyze the relationship between corporate governance and climate policies. However, climate change is different from a typical governance issue characterized by conflict of interests between shareholders and managers, because the nature of the issue is a "tragedy of the commons" (free rider) and even a "tragedy of the horizon" problem (Carney, 2015), with the costs of climate actions borne today by individual firms but the benefits to be enjoyed globally by future generations. In contrast, managerial beliefs can transcend economic considerations and help solve the coordination problem which is needed to tackle the challenging issue of climate change facing our time. As such I also add to the growing literature on the relationship between managerial beliefs and corporate policies (e.g., Bernile et al., 2017; Di Giuli and Kostovetsky, 2014; Hilary and Hui, 2009; Malmendier et al., 2011). I distinguish from these studies by focusing on climate policies.

One primary challenge for empirical research is endogeneity (Adams et al., 2010; Garcia-Castro et al., 2010; Hong et al., 2012). From this perspective, this study also contributes to the literature by analyzing a determinant of climate policies that is clearly exogenous. To the extent that locally incurred natural disasters are not expected to significantly affect the performance of large firms, the significant impact of natural disasters on climate ratings also allows me to use the IV method to tackle reverse causality and study the causal impact of climate actions on firm performance, which adds to this nascent literature (Delmas et al., 2015; Matsumura et al., 2014).

From the public policy point of view, the evidence in the paper suggests a strategy to educate executives about the severity of ACC. If one can design a simulation that enables executives to experience the devastating impacts of natural disasters that are likely to happen to their residing areas if GW continues (Myers et al., 2013), then the results in the paper suggest that they are more likely to take climate-friendly corporate actions.

The remainder of the paper is organized as follows. Section 2 describes the data, sample, variables, and summary statistics. Section 3 examines the effect of natural disasters on climate ratings, and test three hypotheses that may explain the results. Section 4 examines the causal effect of climate ratings on firm performance. Section 5 conducts several robustness checks. Finally, Section 6 concludes.

2. Sample, Variables, and Summary Statistics

2.1. Data and Sample

The sample used in the empirical analysis was an intersection of several databases. The CSR data are from the MSCI ESG (Environmental, Social, and Governance) STATS database, which rates the CSR policies of the largest publicly traded firms in the U.S. including climate policies. The accuracy of the MSCI data was confirmed by several studies (e.g., Chatterji et al., 2009; Sharfman, 1996). Its coverage has expanded over time, starting at 1991 with around 650 firms to around 3,000 firms from 2003 on. My MSCI data ends at 2012. The data cover more than 60 ESG indicators in seven categories: environment, community, human rights, employee relations, diversity, customers, and governance. The database also includes involvement data for some controversial business issues (CBI) such as alcohol and tobacco. I follow most CSR studies and exclude CBIs from the analysis. The MSCI ratings are reported at the end of calendar years.

The data on natural disasters are from the NOAA Storm Events Database, which records severe meteorological events at the county level in the U.S. Appendix A lists the major disaster types covered by the database. The comprehensive coverage of these disasters started at 1996. The database is best at recording short-duration events such as storms but is deficient in the coverage of drought due to its protracted length. Because drought is an important disaster type related closely to climate change, I replace the drought data in the Storm Database with those from the crop insurance data provided by the United States Department of Agriculture (USDA).[11]

The financial data are from COMPUSTAT, including the information on headquarter counties. One drawback of the COMPUSTAT data is that it lists only the headquarters at the date when the data is extracted, which are years 2006, 2011, and 2014 in my case. To reduce the measurement error, the headquarters for the years prior to 2006, between 2007 and 2010, and 2012 are assumed to be the same as those of 2006, 2011, and 2014, respectively.[12] I realize this does not completely solve the measurement issue but note that empirically speaking few firms move their headquarters.

[11] To alleviate the concern for sample selection because of the voluntary nature of crop insurance purchase, and the mismatch between crop and headquarter counties, I calculate the annual number of droughts for a headquarter county as the sum of annual unique droughts within 100 kilometers (kms) radius of the county. I use the Haversine formula to calculate the great-circle distance between two places on a sphere. The formula is given by $d_{12} = R \times 2 \times \arcsin(\min(1, sqrt(h)))$, where R is the earth's radius (approximately 6371 kms), $h = \left(\sin\left(\frac{\Delta lati}{2}\right)\right)^2 + \cos(lat_1) \times \cos(lat_2) \times \left(\sin\left(\frac{\Delta longi}{2}\right)\right)^2$, $\Delta lati = lati_1 - lat_{i2}$, $\Delta longi = longi_1 - longi_2$, and $lati$ and $longi$ are the latitude and longitude of a county, respectively. I also entertain setting the radius from a headquarter county to be 200 and 300 kms, and obtain similar results. The choice of 100 kms for the radius is based on a balance between the requirement for a fine area of geographic resolution for disasters and the need to include at least one county with crop insurance within the radius.

[12] Results are qualitatively similar if I assume the headquarters at a year without data are the same as those closest to that year with the data available. That is, headquarters for the years prior to 2006, and for the years 2007 and 2008 are assumed to be the same as those of 2006, and the headquarters for the years after 2008 including 2012, are assumed to be the same as those of 2011. The only difference is that when using the IV method climate ratings become weakly positively related to Tobin's Q instead of being insignificant. But the results using the political atmosphere associated with the Obama election in 2009 as a quasi-natural experiment to exogenously increase climate ratings still show an insignificant impact of climate ratings on firm performance.

Among those who do, most are changing locations within the same Metropolitan Statistical Areas (MSAs), which should not impact the results since the natural disasters in my sample are most likely to affect the entire MSAs. For example, Pirinsky and Wang (2006) show that among around 5,000 firms in their sample, only 118 relocated their headquarters to a different MSA. In my sample, only around 5% of the firms relocated their headquarters to places that are at least 100 kilometers away from their original locations between 2006 and 2014. To further examine this issue, I manually collect the headquarter location data for the S&P 500 firms of 2006 for the years between 1999 and 2012. I find that the results using this sample are qualitatively similar.

In testing the ACH I employ the Institutional Shareholder Service (ISS, formerly RiskMetrics) Database for some proxies of the lax monitoring of management. The ISS data cover the director composition and antitakeover provisions of the S&P 1,500 firms. I do not control for these governance variables in the primary models to preserve sample size. In unreported analysis I find that the results are similar with the inclusion of these variables.

Even though climate ratings are reported at the end of a calendar year, climate policy decisions can be made earlier in the year. Therefore, I lag the disaster variable by one year in the analysis to rule out the possibility that some disasters may take place after the decision on climate policy is made. To alleviate the concern for endogeneity, all the control variables are also lagged by one year.[13] Because one of the climate policy variables (Climate concern) started at 1999, after merging different sources of data the final sample covers the period between 1999 and 2012 with 22,642 firm-year observations, 3,360 firms, and 546 headquarter counties.

2.2. Variables

I describe the major variables in this section. The detailed definitions are in Appendix B.

[13] The results are robust to using the contemporaneous levels of the disaster and control variables.

2.2.1. CSR Related Variables

The MSCI CSR ratings are a binary variable indicating either strength or concern. According to the user guide, the strength/concern is assigned a value of 1 if a company meets the criteria established for a rating, and 0 otherwise.

I focus on two climate policy related ratings in the corporate environmental responsibility (CER) category of the MSCI data: Climate strength and Climate concern. Appendix C provides a detailed description of these variables. The definition of Climate strength suggests a potentially wide range of industries for which this variable may be relevant. For example, a retailer may have a strength rating if it takes actions to reduce carbon footprint in its supply chain. In contrast, Climate concern is relevant only for industries with "material" risk of climate change, such as oil, utility and transportation industries.[14]

I subtract Climate concern from Climate strength to calculate a firm's net climate rating (Climate rating). This is similar to the way that many studies measure a firm's net CSR rating by subtracting the (raw or adjusted) sum of the CSR concern indicators from the (raw or adjusted) sum of the strength indicators (e.g., Benson and Davidson III, 2010; Cai et al., 2011; Goss and Roberts, 2011; Harjoto et al., 2017; Jo and Harjoto, 2012). I examine the appropriateness of defining climate rating this way in Section 2.3. This measure of climate rating suggests that it could take on three values: -1, 0, and 1. I create two additional variables from the MSCI data to consider the fact that CSR investments are typically clustered, one with all the ratings in CER other than Climate rating (Net CER), and the other with all the CSR ratings in categories other than

[14] In unreported analysis, I study the potentially differential impact of natural disasters on climate ratings depending on whether climate risk is material for an industry or not based on the materiality map of the Sustainability Accounting Standards Board (SASB) (https://www.sasb.org/materiality/sasb-materiality-map/). I do not find a significant difference.

environment (Net CSR).[15] Because the availability of the MSCI data changes over time, the extant studies have employed different ways to define net CSR. In my primary specification I follow Benson and Davidson III (2010) to define Net CER and Net CSR. In Section 5 I examine the robustness of the results using other definitions of these variables.

2.2.2. Natural Disaster

I include different types of weather events in the disaster measure primarily for two reasons. First, the existing climate models involve some uncertainties on the changes in the frequency and magnitude of the specific types of extreme weather associated with ACC. Second, empirically it is not clear which types of disasters may matter for managerial beliefs in ACC. For that purpose I include all the disasters that are possibly connected to GW (Melillo et al., 2014), and exclude only those that are clearly not relevant such as extreme cold/wind chill, tsunami and rip current. The specific meteorological events included in the primary measure of the disaster variable (Disasters) are heat events, wildfires, droughts, floods, hurricanes/tropical storms, tornadoes, and winter storms.[16] Each of these categories may further include multiple types of disasters. For example, hurricanes/tropical storms and tornadoes may include strong wind, thunderstorm wind, tornado, lightning, hail, and high wind. The specific events included or excluded in the definition of Disasters are listed in Appendix A. In Section 5 I entertain different measures of the disaster variable to corroborate the major findings. To facilitate interpretation, I follow Di Giuli and Kostovetsky (2014) to standardize Disasters to have a mean of 0 and standard deviation of 1.

2.2.3. Firm Performance

[15] The results are robust to whether I include the governance category in the calculation of Net CSR.
[16] Snow storms may become more frequent and intense due to GW, because warmer weather means more moisture in the atmosphere. There is also some evidence that the U.S. has seen more frequent and intense winter storms since the 1950s (Melillo et al., 2014).

I use Tobin's Q to measure firm performance. In untabulated analysis I also examine accounting-based performance measures such as ROA and ROE, and find similar results.

2.2.4. Control Variables

Since climate policies are part of CSR, I also include a number of financial controls in the regressions following the literature on the determinants of CSR (Aggarwal and Dow, 2012; Di Giuli and Kostovetsky, 2014; Jiraporn et al., 2014). These variables include firm size, sales growth, ROA, leverage, dividend payout, capital expenditure, R&D expense, advertising expenditure, and cash balance. The controls in the Tobin's Q regressions are similar. All the control variables are winsorized at the 1st and 99th percentiles to reduce the influence of outliers.

2.3. Summary Statistics

In Figure 1 I plot the time trend of climate ratings. It is apparent that climate rating was quite stable until 2010, when it experienced a "jump". The jump is presumably due to the political atmosphere at the time with the election of Barack Obama as the U.S. President, who is a strong advocate of ACC.[17] It is plausible that firms took actions to reduce GHG emissions after his election in anticipation of the possible regulations under him. In Section 4 I use the election of Obama as a quasi-natural experiment to exogenously increase the climate ratings, and examine the causal effect of climate ratings on firm performance.

Insert Figure 1 about here

Table 1 reports the summary statistics of the major variables in the study. The statistics in Panel A show sparse incidences of climate strengths and concerns with a mean of 0.07 and 0.05, respectively, resulting in a mean climate rating of 0.02. It is possible that for many industries

[17] Obama advocated for ACC since his campaign trail and attempted to pass American Clean Energy and Security Act in 2009, but eventually failed at the Senate. He then launched the Clean Power Plan in 2015, an initiative at the executive branch level (EPA) rather than through legislations. Under his administration, the U.S. also entered into the Paris Agreement in 2015, an international effort to reduce GHG emissions.

climate policies are simply not “material”. To examine this possibility, in Panel B I list the average climate strength, concern, and net rating by industries. I use two-digit SIC codes to characterize industries throughout the paper. Industries with fewer than five firms are excluded. Consistent with earlier discussions on the more industry relevance of climate strengths than concerns, the statistics show far more incidence of industries with no climate concerns than strengths. In untabulated analysis I find that the results are robust to excluding the industries with no climate strengths, or no climate concerns, either no climate strengths or climate concerns, or both. It is apparent from Panel B that for most industries climate strength policies are relevant. The industries with significant climate concerns are largely consistent with the “materiality map” of the Sustainability Accounting Standard Board (SASB). Interestingly, for some industries with high climate concerns, climate strengths seem also significant, presumably reflecting the fact that some firms engage in CSR in an attempt to reduce the potential liabilities of corporate social irresponsibility (Jo and Na, 2012; Kotchen and Moon, 2012). Indeed, I find that the correlation between Climate strength and Climate concern in my sample is 0.12 and highly significant. These results raise the concern that though a firm with both climate strength and concern may be fundamentally different from another firm whose climate policies are not relevant, these two firms nonetheless have the same climate rating of zero. As it turns out, out of the 22,642 observations in the sample, 228 firm-years have both climate strengths and concerns. In unreported analysis, I find that the results are robust to excluding these observations from the sample.[18] The statistics in Panel A also show sparse incidences of other CSR ratings, as indicated by low averages of Net CER and Net CSR.

Insert Table 1 about here

[18] In another untabulated analysis, I study the impacts of natural disasters on climate strength and concern individually. I find that the effect of disasters on Climate strength is slightly stronger than that on Climate concern, but the results are consistent with each other in that disasters positively impact climate strength and negatively impact climate concern. Therefore, combining the two indicators by taking their difference seems appropriate in this study.

Panel A also reports the statistics on the raw disasters as well as their standardized value. The average annual number of disasters in the sample is 23.31, with a standard deviation of 17.44. The statistics are similar using a county-level sample which keeps only one observation for multiple firms headquartered in the same county in a year, with a mean of 22.91 disasters and a standard deviation of 16.24. This county-level sample helps reduce the possibly undue influence of some counties where headquarters are clustered. More importantly, the statistics also show that out of the standard deviation of 16.24, 14.24 comes from cross-sectional variation and 5.98 is due to the variation over time. The latter variation is critical for the implementation of fixed-effects (FE) models, which I employ as the primary specification in this study (Zhou, 2001). Relying on within-county variations, the FE models are consistent with the notion that, rather than worrying about the different *levels* of natural disasters at different locations, managers are more concerned about the *change* in disasters at a specific location as a sign of ACC.

The summary statistics for the control variables largely accord with prior studies, with some differences presumably driven by different sample periods and industry inclusions (e.g., Di Giuli and Kostovetsky, 2014; Jiraporn et al., 2014). The sample in this study is noticeably larger and covers a longer and more recent time period.

3. Natural Disasters and Climate Rating

In this section I first examine the impact of natural disasters on climate ratings. I then test three hypotheses that may explain the results.

3.1. The Effect of Disasters on Climate Rating

I employ the FE model as the primary specification because it both helps reduce the omitted variable bias, and relies on time variations of disasters which accord better with the nature of climate change than cross-sectional difference in disasters. To verify this, I compare the results based on OLS models with those with county FEs. To further alleviate the omitted variable bias, I also include the firm FEs. The fact that climate ratings are ordinal numbers suggests that it is best to employ the ordered probit/logit models in the analysis. However, the inclusion of the FEs suggests that this is infeasible to do because of the “incidental parameter” problem (Neyman and Scott, 1948). Therefore, I employ linear models with FEs as my primary specification, and use ordered probit/logit models whenever possible to examine the robustness of the results. In all the models, I also control for industry and year effects. Standard errors are adjusted for heteroskedasticity and clustered at the firm level (Petersen, 2009).[19]

I first use matched pairs to examine the effect of natural disasters on climate ratings. I conduct two types of matching to illustrate the importance of including FEs in subsequent regressions. First, relying on cross-sectional variations of disasters, I match firms sustaining more disasters with those sustaining fewer disasters than the sample median by industry and size. This process generates 10,632 matched pairs. The second matching process is similar, except that the disasters are *county de-meaned*. This results in 12,448 matched pairs.[20] Because climate ratings are at the firm level, I calculate the firm de-meaned climate rating in the second matched sample. I conduct a *t*-test for the difference between the raw or firm de-meaned climate ratings based on the two matched samples, respectively. The results are presented in Panel A of Table 2.

Insert Table 2 about here

The results in Panel A confirm the importance of within-county, rather than cross-sectional variations of natural disasters in their relationship with climate ratings. While the difference between climate ratings is insignificant for the sample based on cross-sectional variations, it is

[19] Results are qualitatively similar if clustering the standard errors at both the firm and county levels.
[20] The sample size is greater than 22,642 firm-years as reported earlier because in this step I do not enforce the requirement that all the control variables are available.

highly significant for the sample based on within-county variations of disasters. Specifically, the results suggest that an *increase* in the disasters of a county relative to the average value of the county over time results in an *upgrade* of the climate rating of a firm headquartered in that county relative to the average rating of the firm over time.

In Panel B I run regressions to formally examine the relation between natural disasters and climate ratings. In Model 1 I report the OLS results without any control variables.[21] The coefficient on Disasters is almost zero and is not significant. In Model 2 I add the county FEs. Interestingly, Disasters becomes positive and highly significant at the 1% level. The contrast between the results in the two models accords with the *t*-test results in Panel A, which suggests that within-, rather than between-county variations of natural disasters drive their positive impact on climate ratings. In Model 3 I add the two CSR variables, Net CER and Net CSR, which are positive and highly significant. This suggests that firms often engage in multiple CSR activities at the same time. The coefficient on Disasters and its significance are almost identical to those in Model 2. The same is true when I add financial controls in Model 4. In Model 5 I further add the firm FEs. The coefficient on Disasters is slightly smaller compared to Model 2 but is still highly significant. It is also notable that between Models 4 and 5 some control variables either switch signs or lose significance. This is puzzling and worth investigating in a future study.

Turning to the economic significance of the results, the coefficient on Disasters in Model 5, 0.014, suggests that on average increasing the annual number of natural disasters at a county by one standard deviation (5.98) results in an upgrade of the climate rating by 0.0048 (=0.014*5.98/17.44) notch. This may seem small. But note that the average climate rating in the sample is only 0.02. Therefore, the 0.0048-notch actually represents a substantial 24%

[21] The results are similar if adding the control variables in the regression.

improvement in the rating of the average firm. Assuming that the impact of disasters on the probability of improving climate ratings is linear, this also suggests that a one standard deviation of an increase in disasters at a county increases the probability of adding climate strength/eliminating climate concern by a firm headquartered in that county by 24%. This effect is even stronger than some of the financial variables such as sales growth and ROA.

The "incidental parameter" problem as stated before causes the estimates of ordered probit/logit models to be inconsistent due to a large number of FEs. This issue is severer for firm FEs because there are far more firm FEs than county FEs (3,360 firms vs. 546 counties). Therefore, in Table 3 I employ ordered probit and probit models with only county FEs to examine the robustness of the results. I test the effects of Disasters on Climate rating, as well as on Climate strength and Climate concern individually. The results corroborate those using linear models – disasters continue to positively (negatively) impact Climate rating and Climate strength (Climate concern) of a firm.[22]

Insert Table 3 about here

In unreported analysis, I also examine the effects of natural disasters on other CER ratings. I find that only the concern rating on hazardous waste (env_con_a in MSCI) is significantly affected by disasters using the linear model. However, the result is not robust with a probit model or including a narrower set of weather events that are more closely related to climate change in the definition of the disaster variable. In contrast, I show in Section 5 that this alternative measure of disasters continues to affect climate ratings significantly. Collectively, the results suggest that, among all the CER policies of a firm, only climate policies are significantly impacted by natural disasters, which is consistent with the different natures of different environmental actions.

[22] The results are similar using ordered-logit and logit models. The economic significance as suggested by Table 3 is also comparable to that based on the linear models. For example, the coefficient on Disasters in Model 2 suggests that, for an average firm in the sample, increasing the annual number of disasters at a county by one standard deviation and keeping all other variables at their sample means increases the probability of having climate strength by 27%.

Given the increasing popularity of the issue of ACC and its likely disastrous impact on humans, it is reasonable to believe that though firms may choose more climate-friendly policies with an *increase* in disasters, they may not *disengage* in climate actions when disasters *decrease*. To examine this possibility, I first eliminate the county and firm FEs by running regressions on the county and firm de-meaned variables. I then interact the county and firm de-meaned Disasters with an indicator for whether the county de-meaned Disasters is above the sample median (More county de-meaned Disasters).[23] If disasters have an asymmetric impact on climate ratings, this interactive term is expected to be positive and significant. The results are reported in Table 4. Model 1 without the interactive term confirms the results in Table 2.[24] Consistent with expectations, the interactive term in Model 2 is positive and significant, suggesting that an *increase* in disasters has a stronger impact on climate ratings than a *decrease* in disasters. More importantly, the results also show that after the interactive term is controlled for, De-meaned Disasters itself loses significance. In undocumented analysis I show that the differential effect of disasters on climate ratings remains if running regressions on the two sub-samples characterized by more or fewer county de-meaned disasters separately. Collectively, these results demonstrate an asymmetric impact of disasters on climate ratings, that while an increase in disasters motivates managers to take climate-friendly actions, a decrease in disasters does not have the countervailing effect.

Insert Table 4 about here

3.2. Belief Hypothesis

As discussed above, a positive impact of locally incurred natural disasters on corporate climate policies is consistent with the BH, that experiencing extreme weather strengthens beliefs in ACC

[23] The results are similar if the indicator variable is based on whether Disasters at a given year is above the county average. The results are also robust to defining the indicator variable relative to county *and* firm de-meaned Disasters.
[24] They are not identical because the industry and year effects are not de-meaned.

and motivates managers to take climate-friendly actions. But both the ACH and RRH may also explain the result, and they each have support in other context involving CER or CSR (Barnea and Rubin, 2010; Cai et al., 2016; Cheng et al., 2016; Matsumura et al., 2017). Between the two hypotheses, the RRH is less likely because I focus on locally incurred disasters but RRH is more plausible for "mega-disasters" that cause substantial damages in a wide area. Nonetheless, some of the local disasters may also be "mega-events" (such as Hurricane Katrina and Hurricane Sandy). Therefore, I also examine RRH in this study. It is worthwhile to point out that the three hypotheses are not mutually exclusive. A manager may become more convinced about ACC when experiencing natural disasters, while at the same time using it as an excuse to take climate actions to benefit himself at the expense of shareholders. Therefore, the evidence I present below in support of a specific hypothesis does not automatically reject the other ones. I examine the BH in this section, and the ACH and RRH in the next two sections.

I examine two aspects of a belief in ACC to test BH. First, Bayesian updating suggests that experiencing extreme weather should have a stronger effect on a manager who was initially suspicious of ACC (Deryugina, 2013). I identify two types of managers who are likely to have weaker beliefs in ACC based on the extant literature, Republicans and males (Borick and Rabe, 2010; Egan and Mullin, 2012; McCright and Dunlap, 2011; Shao et al., 2014). I then follow Compton et al. (2016) to define a "Red state" dummy that equals one if the votes for the Republican candidate in a presidential election in a state exceed those for the Democratic candidate.[25] Since there is a four-year interval between two consecutive elections, I assume Red state at a year with no presidential election to be the same as its value in the most recent election. I also create a More

[25] The studies referenced above typically use surveys to identify the political leaning of respondents. I lack such data in this study. Using the headquarter state to identify the partisan beliefs of managers essentially assumes that the political environment of a state influences its residents. This is similar to the studies using the religious adherents of the headquarter state/county of a firm to identify the religiosity of its managers (e.g., Hilary and Hui, 2009).

male directors dummy that equals one if the lagged percentage of male directors on a board is above the sample median, and zero otherwise. The data for state votes in presidential elections and board compositions are from Dave Leip's Atlas and ISS, respectively. Because ISS covers S&P 1,500 firms, the sample size is smaller when examining whether director gender has an influence on the effect of natural disasters on climate ratings. I interact Disasters with Red state and More male directors, respectively. If the BH holds, these interactive terms are expected to be positive and significant. The results are reported in Models 1 & 2 of Table 5.

Insert Table 5 about here

Indeed, the results in these models provide support to the BH. Both interactive terms, Disasters * Red state and Disasters * More male directors are positive and significant. The results also show that Red state is negative and weakly significant, suggesting that on average the climate ratings of the firms located in Republican-leaning states are lower than those in Democratic-leaning states. This result is consistent with Di Giuli and Kostovetsky (2014), who find that Republican-leaning managers generally engage less in CSR activities. Subsequently I use Red state as one of the IVs to examine the causal impact of climate ratings on firm performance.

The second aspect of a belief in ACC that I examine is on a possibly stronger concern for ACC for managers residing in places that are predicted to incur greater losses because of ACC. Specifically, coastal and southern areas are expected to suffer the greatest from GW because of sea level rise and warmer weather (Hsiang et al., 2017; IPCC, 2012a; Lloyd's, 2014). Counties with more populations may also suffer more because of more stakes at risk. To examine these possibilities, I obtain data for coastal counties from NOAA's Office for Coastal Management,[26] and county latitude and population data from the 2010 Census Gazetteer Files. I then create dummy

[26] I exclude the counties located by the Great Lakes. Results are similar if including them as coastal counties.

variables to indicate whether a firm is headquartered in a coastal, southern, or more populous county. The latter two dummies are defined relative to their respective sample medians. I then interact Disasters with these dummy variables separately. The results are presented in Models 3-5 of Table 5. Consistent with the predictions of the BH, the three interactive terms are all positive and significant, suggesting that managers residing in places likely to fare worse due to ACC are more apt to take climate-friendly actions when experiencing extreme weather. Interestingly, the southern county and high population dummies are negative and significant, which suggests that on average firms located in the south and more populous areas engage less in climate actions, despite the fact that their locations are expected to suffer more from climate change.

Collectively, the results in Table 5 suggest that managers who are initially skeptical of ACC and whose firms are in a location likely to sustain greater damages because of ACC, seem to update their beliefs in ACC more and are more likely to take climate actions when experiencing natural disasters. These results are consistent with the predictions of the BH.

3.3. Agency Cost Hypothesis

The ACH is based on the idea that climate policy is an agency problem and managers use the incidence of natural disasters as an excuse to take actions to benefit themselves but hurt shareholders. Managers should find it easier to do so if shareholder monitoring is weak. I thus examine this hypothesis by testing a differential impact of disasters on climate ratings conditional on different strictness of monitoring. I rely on existing studies for indicators of weak monitoring. First, there is extensive evidence of larger and classified boards being less effective in performing their monitoring functions (Bebchuk and Cohen, 2005; Cohen and Wang, 2013; Hermalin and Weisbach, 2003). On the other hand, Coles et al. (2014) show that “co-copted boards” with more directors elected after the incumbent CEO took helm are associated with weak monitoring, presumably because of their allegiance to the CEO. Agrawal and Nasser (2012) show that independent directors with substantial stock ownership are good monitors, hence boards without independent "blockholders" may not be effective. Finally, Jensen (1986) argues that debt is important to reduce the agency costs of free cash flows. Less debt thus indicates the lack of managerial discipline. I then create dummy variables based on these proxies of weak monitoring similar to the methodology used in testing the BH. Specifically, Classified board dummy equals one if a board was classified in the previous year, and zero otherwise. No ind blk dummy is equal to one if a firm did not have an independent director with at least 1% ownership in the previous year (Agrawal and Nasser, 2012), and zero otherwise. The dummy variables based on the other three proxies of lax monitoring are generated by comparing a firm's lagged value of the proxy to its sample median. I then interact these dummy variables with Disasters respectively in the regressions. The ACH would predict positive and significant interactions. However, the results in Table 6 show that except for the interaction involving Classified board, all other interactive terms are not significant. Disasters * Classified board is positive and significant as predicted by the ACH. In unreported analysis, however, I find that this term loses significance if the weather events included in the definition of the disaster variable are restricted to those that are more likely to increase with ACC (IPCC, 2012b; Melillo et al., 2014).[27] Therefore, the evidence presented in Table 6 does not provide strong support to the ACH.

Insert Table 6 about here

3.4. Regulatory Risk Hypothesis

If managers take climate actions to reduce the potential liability of regulations or litigations that may arise as a result of the natural disasters, it is expected that they have a stronger incentive to do

[27] The results using this alternative measure of disasters continue to support the BH, but not the other two hypotheses. Under this measure of disasters, the evidence in support of the BH is stronger.

so if the perceived risk of regulations or litigations before the disasters is higher. I use several proxies for this risk at both the federal and state levels to test the RRH. First, since Democrats are generally advocates of ACC (Wallach, 2012), the time period under a Democratic President should entail a higher risk of regulations. Therefore, my first proxy for regulatory risk is a time dummy, Democrat pres, that equals one if the incumbent president is a Democrat.[28] Second, if a state had already incurred substantial damages from disasters in the preceding year, subsequent disasters should make the regulations more likely. To estimate the economic damages incurred by a state, I utilize the NOAA Billion-Dollar Disasters Database which reports the inflation-adjusted total damages caused by natural disasters resulting in at least $1 billion loss, and the states that are affected by these disasters (Smith and Katz, 2013). State damages are estimated to be proportional to their GDPs and are summed over all the disasters affecting the state in a given year.[29] I then create a dummy variable, High disaster loss, that equals one if the lagged value of the estimated state damages in the previous year exceeds the sample median, and zero otherwise. Third, because the Deepwater Horizon oil spill in 2010 was a major environmental accident, it is expected that the risk of regulations is higher after this incident. The dummy variable, Post Deepwater equals one if the year is on or after 2010, and zero otherwise. Finally, different industries may have different risk of litigation by nature of their operations. Since climate concern is measured partly by litigations, I create a dummy variable, High litigation risk, that equals one if the fraction of firms with climate concerns in an industry in the previous year is above the sample median, and

[28] If instead managers are concerned about state legislations as a result of natural disasters, the positive interactive effect of disasters with red state dummy as presented in Table 5 already shows that if a state is leaning toward the Democrats, the effect of natural disasters on climate ratings is weaker, which is inconsistent with the RRH.

[29] The Billion-Dollar disasters data is available at: https://www.ncdc.noaa.gov/billions/events/US/1980-2017. I delete the disaster "freeze" from the data because it is not closely related to GW. 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/or the web. The data for state GDP is from Bureau of Economic Analysis (BEA).

zero otherwise. I then interact each of the dummy variables as defined above with Disasters in the regressions. If the RRH holds, these interactive terms should be positive and significant. The results are reported in Table 7.

Insert Table 7 about here

The results in Table 7 show that none of the interactions is positive and significant, inconsistent with the RRH. Except for Disasters * Democrat pres, all other interactions are insignificant. Disasters * Democrat pres is negative and weakly significant, directly contradicting the hypothesis. It is also notable that both Democrat pres and Post Deepwater are positive, suggesting that more firms engage in climate actions under a Democratic president and after 2009. I note that the latter result is consistent with the jump of climate ratings at 2010 as shown in Figure 1.

Collectively, the results presented in tables 2-7 demonstrate a strong effect of locally incurred natural disasters on climate ratings, which is best explained by the idea that experiencing extreme weather enhances beliefs in ACC and motivates managers to take climate-friendly corporate actions. The results do not support the hypothesis that managers use disasters as an excuse to take climate actions at the expense of shareholders. Nor do they support the notion that managers adopt climate-friendly policies to mitigate the risk of regulations or litigations in response to disasters. It is important to point out that the lack of support for ACH and RRH does not necessarily refute the claims that climate policies are an agency problem and can reduce the risk of liabilities. What these results demonstrate is that even if climate actions may serve these functions, locally incurred natural disasters seem not have played an important role in inducing these actions through them.

4. Climate Rating and Firm Performance

As stated, the issue of climate change is essentially an issue of the "tragedy of the commons" or even "tragedy of the horizon". Therefore, even if the results thus far suggest that managerial belief matters significantly in combating ACC, it is unclear whether climate actions ultimately benefit or hurt firm performance. If a firm internalizes the externality caused by GHG emissions by taking climate actions, it could well hurt its performance. On the other hand, because of the high-profile publicity of the issue of ACC (e.g., Bauerlein, 2006; Gillis, 2016; Khan, 2017; Shabecoff, 1988; Wilford, 2000), and the uncertainty on regulations, adopting climate-friendly policies may help a firm ameliorate relationship with its stakeholders and reduce potential liabilities hence improving performance. Therefore, the relationship between climate actions and firm performance is ultimately an empirical issue. Two notable studies, Matsumura et al. (2014) and Delmas et al. (2015) find a negative association between GHG emissions and firm performance, suggesting that climate-friendly actions benefit firms. However, both studies are based on cross-sectional variations of the variables and hence are subject to the concern for endogeneity. I examine the impact of climate ratings on firm performance in this section, especially in light of this concern.

I first use an OLS model as the baseline result, as reported in Model 1 in Panel A of Table 8. The results show a positive and weakly significant association between climate ratings and Tobin's Q, consistent with Matsumura et al. (2014) and Delmas et al. (2015). However, when I further control for firm and county FEs in Model 2, Climate rating changes sign and becomes more significant. This result contrasts with Delmas et al. (2015) based also on the FE model. Except for different measures of climate policy variables, another potential reason for the difference is that this study has a larger sample and longer time period.

Insert Table 8 about here

Both OLS and FE models are subject to the concern of reverse causality. I employ the IV method based on the FE model to tackle this issue. A valid IV needs to satisfy two conditions: (1)

relevance, that it must be related to climate ratings; and (2) exclusion, that it cannot directly affect firm performance. Its association with firm performance must be through climate ratings. The results thus far suggest two potential IVs: Red state and Disasters.[30] The Republican strength has been used as an IV for CSR in prior studies (e.g., Cornett et al., 2016; Deng et al., 2013; Goss and Roberts, 2011). Given the significant impact of Disasters on climate ratings, whether it can serve as an IV hinges critically on whether disasters can directly affect firm performance. In general, this is plausible given the potential damages caused by disasters. In this case, however, since I focus on locally incurred disasters and firms are very large, it is unlikely that disasters will significantly impact firm performance. Therefore, disasters in this context may serve as an effective IV for climate ratings. The first and second stage results using the IV methodology are presented in Models 3 and 4 in Panel A of Table 8, respectively. In contrast to the results in Models 1 and 2, Model 4 shows that climate ratings do not significantly affect firm performance. The Hansen overidentifying test statistic suggests that the IVs are valid.

The time pattern of climate ratings as observed in Figure 1 suggests another potential method to test the causal impact of climate ratings on firm performance. As stated, it is plausible that the Obama election has pushed many firms to voluntarily take climate actions in anticipation of possible regulations. If this is true, the Obama election may serve as a quasi-natural experiment to exogenously increase climate ratings, hence allowing the use of difference-in-differences (DID) methodology to examine a causal impact of climate ratings on firm performance. However, because this experiment is based on political atmosphere and not actual regulations, it is not straightforward to identify the "treatment" and "control" groups, which are needed in the DID implementation. I use the following method to identify the "treatment" firms, which are the firms

[30] Results are similar if using Disasters as the only IV.

that are likely to have exogenously increased their climate investments after the Obama election. First, I run regressions on Climate rating similar to Model 5 of Table 2,[31] but only for the period on or before 2009, the year right before the jump of climate ratings. I then use the estimated coefficients based on this model to predict the value of Climate rating at 2012, which represents the likely value of the rating without the Obama election, and calculate the "excess climate rating at 2012" as the difference between the actual rating and this predicted value. Finally, I identify the treatment firms based on two criteria: 1. they have positive excess climate ratings at 2012; and 2. their ratings were indeed upgraded between 2009 and 2012. The control firms are defined as those that did not experience a change in climate ratings during this period.[32] I then match each treatment firm with a control firm by industry and the predicted value of climate rating at 2012.[33] The latter is used as a matching criterion because it represents the likely value of the climate rating in absence of the treatment. It turns out that there are 173 matched pairs of treatment and control firms. I first examine the difference between the changes in Tobin's Q between 2009 and 2012 of the matched pairs In Panel B of Table 8. The *t*-statistics as shown do not detect a significant difference. I then use a first-difference (FD) regression model on the matched sample with control variables to further examine the effect of climate ratings on firm performance. The results are presented in Model 5 of Panel A in Table 8. Consistent with the *t*-test results, the FD regression results are also insignificant. These results confirm those based on the IV methodology.

Collectively, the results in Table 8 suggest that the effect of climate ratings on firm performance depends critically on model specifications, with OLS and FE models generating directly opposite

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[31] Results are similar if I include only the control variables that are significantly related to climate ratings. This can increase the number of treatment and control firms.

[32] I do not include the firms whose climate ratings were downgraded during this period in the control group because given the political environment at the time, the actions of these firms may be the result of responding to other factors rather than being exogenous. The results are similar if including these firms in the control group.

[33] The results are similar if I match the treatment and control firms based on industry and firm size.

results. Using methods presumably less susceptible to the concerns of endogeneity, climate ratings seem not to significantly affect firm performance.

5. Robustness Checks

I conduct several robustness checks in this section to buttress the major findings in this paper.

5.1. Economic Damages of Disasters

One drawback of using the frequency of natural disasters to measure their influence on managerial belief in ACC is that it ignores the severity of disasters. 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 due to "mega-disasters". Using the methodology as described in Section 3.4 I estimate a state-level damage variable due to all the "mega-disasters" in a given year. I then "normalize" this variable using the state GDP at 2012 to arrive at the Billion disaster loss variable (e.g., Pielke Jr. et al., 2008; Simmons et al., 2013). The normalization takes account of the different levels of wealth at stake at different points in time. I examine the relationship between this disaster measure and climate ratings in Model 1 of Table 9. To be consistent with the state-level disaster variable, I replace the county FEs with the state FEs.

Insert Table 9 about here

The results show that Billion disaster loss is positive and highly significant, consistent with the results based on the frequency of disasters. Note that the average climate rating of this sample is 0.008 and the within-state standard deviation of the disaster loss is $1.72 billion. Therefore, the coefficient on the loss variable, 0.001, suggests that if the damage to a state from "mega-disasters" increases by one standard deviation, climate ratings are expected to be upgraded by 0.00172-notch, which amounts to 22% of the climate rating of the average firm in the sample. This magnitude of impact of natural disasters is substantial and comparable to that based on the frequency of disasters.

5.2. Alternative Disaster Types

I include heat events, wildfires, droughts, flooding, hurricanes/tropical storms, tornadoes, and winter storms in my primary measure of disasters. The impact of ACC on some of these disasters is more uncertain than others. In this section I examine the robustness of the results by including only the disasters that are more likely to increase with ACC, namely, heat events, wildfires, droughts, and flooding in the definition of the disaster variable (IPCC, 2012b; Melillo et al., 2014). The results as reported in Model 2 of Table 9 show that the disasters closely related to ACC continue to be positive and significant. In unreported analysis I use all the disaster types in the NOAA Storm Database and find the results are also significant.

5.3. Alternative Measures of Net CER and Net CSR

The literature has offered multiple ways to define the net rating of a firm's CSR by subtracing the total count of concerns from that of strengths. In my primary analysis I follow Benson and Davidson III (2010) to define Net CER/CSR. In this section I examine the robustness of the results by using other definitions. I first follow Harjoto et al. (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 3 of Table 9. As shown, the coefficient on Disasters continues to be positive and significant, and the magnitude is even larger than that of Table 2. I untabulated analysis, I define other measures of Net CER/CSR by following Goss and Roberts (2011), Jo and Harjoto (2012), and Cai et al. (2011), respectively. The results are also similar.

6. Conclusion

The substantial stake potentially associated with anthropogenic climate change and the failure to enact federal regulations in the U.S. to limit GHG emissions raises the important question of the factors that determine the climate policies of a firm. This study attempts to address the question by looking at whether personally experiencing natural disasters may enhance managerial belief in ACC, which may ultimately lead to corporate actions to mitigate its impact. The evidence suggests that the effect of disasters on this belief is substantial, which translates into higher rated climate policies. Alternative hypotheses that managers use disasters as an excuse to take climate actions to advance their personal interests, as well as they attempt to fend off the potential liabilities associated with the regulations or litigations that may ensue as a result of these disasters, seem not be able to explain the results well. Finally, using the IV method and the Obama election as a quasi-natural experiment, I do not find a significant impact of climate ratings on firm performance.

Despite the potentially grave consequences of climate change and repeated calls by the United Nations to take actions to combat it, it appears that most firms have not heeded the call. From the public policy point of view, the results presented in this paper suggest a reason for managers to act, and a means to convince them to do so. The fact that climate policies do not hurt firm performance combined with the possibly catastrophic consequences of climate change, suggest a reason for managers to take climate-friendly actions. On the other hand, despite the overwhelming scientific evidence in support of ACC, the fact that personally experiencing natural disasters still matters for climate actions suggests a presumably effective communication strategy to elicit more actions. That is, rather than focusing exclusively on scientific evidence involving mainly analytical processing of information, it may be more worthwhile to design some education programs that permit the simulated experiencing of devastating natural disasters that are predicted to take place with continued global warming.

Appendix A. Disaster Types from NOAA Storm Database

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

Appendix B. Variable Definitions

Variable	Definition	Data Source
Climate strength	Dummy variable that equals one if a firm engages in climate change policies, programs, and initiatives, and zero otherwise (env_str_d).	MSCI ESG STATS
Climate concern	Dummy variable that equals one if there are severe controversies related to a firm's climate change policies, programs, and initiatives, and zero otherwise (env_con_f).	MSCI ESG STATS
Climate rating	Climate strength – Climate concern.	MSCI ESG STATS
Net CER	Lagged value of the total strength count of corporate environmental responsibility (CER) policies excluding Climate strength of a firm scaled by the number of strength items excluding Climate strength in the CER category in a given year, minus the total concern count of CER policies excluding Climate concern of a firm scaled by the number of concern items excluding Climate concern in the CER category in that year.	MSCI ESG STATS
CER net of Climate strength	Lagged value of the total strength count of CER policies excluding Climate strength of a firm scaled by the number of strength items excluding Climate strength in the CER category in a given year, minus the total concern count of CER policies of a firm scaled by the number of concern items in the CER category in that year.	MSCI ESG STATS
CER net of Climate concern	Lagged value of the total strength count of CER policies of a firm scaled by the number of strength items in the CER category in a given year, minus the total concern count of CER policies excluding Climate concern of a firm scaled by the number of concern items excluding Climate concern in the CER category in that year.	MSCI ESG 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 policies 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 policies of a firm scaled by their respective number of concern items in a given year.	MSCI ESG STATS
Raw disasters	Lagged total number of severe meteorological disasters incurred at the headquarter county of a firm in a given year, where the specific disaster types included in the calculation are listed in Appendix A.	NOAA Storm and USDA RMA Crop Insurance
Disasters	Lagged standardized value of raw disasters with a mean of 0 and a standard deviation of 1.	NOAA Storm and USDA RMA Crop Insurance
Size	Lagged value of the log of total sales (log(sale)).	COMPUSTAT
Salesgrow	Lagged value of the log of sales growth (log(sale/lagged sale)).	COMPUSTAT
ROA	Lagged value of return on asset, defined as income before extraordinary items scaled by total assets (ib/at).	COMPUSTAT
Leverage	Lagged value of debt ratio ((dltt+dlc)/at).	COMPUSTAT
Dividend	Lagged value of cash dividends for common and preferred stock scaled by operating income ((dvc+dvp)/oibdp).	COMPUSTAT
Capexp	Lagged value of capital expenditure scaled by total assets, missing values coded as zeros (capx/at).	COMPUSTAT
R&D	Lagged value of R&D expenses scaled by total assets, missing values coded as zeros (xrd/at).	COMPUSTAT
Adver	Lagged value of advertising expenses scaled by total assets, missing values coded as zeros (xad/at).	COMPUSTAT
Cash	Lagged value of cash balance scaled by total assets (che/at).	COMPUSTAT

Q	Lagged value of book value of asset minus book value of equity plus market value of equity, scaled by book value of asset ((at-ceq+prcc_f*csho)/at).	COMPUSTAT

Appendix C. Descriptions of Climate Change Related Variables in MSCI

There are two rating variables that are related to climate change in the MSCI database: Climate strength (env_str_d) and Climate concern (env_con_f). According to the data guide, factors affecting Climate strength 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.*

In contrast, factors affecting the evaluation of Climate concern 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.*

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Figure 1. Time Trend of Climate Rating

This figure shows the time trend of climate ratings. The dot in the figure represents the annual cross-sectional average of the variable. The trend line is based on regressing the annual averages on years.

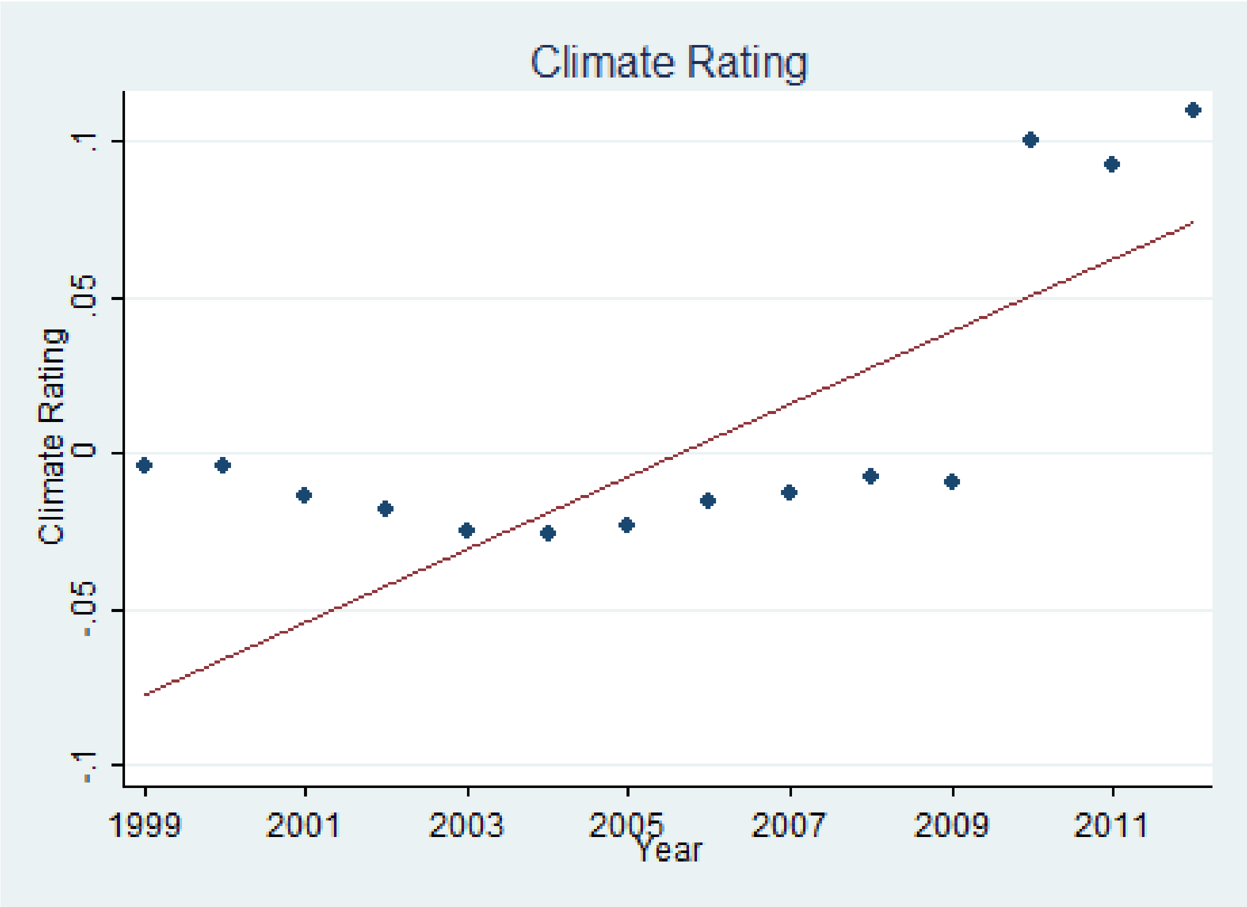

Table 1. Summary Statistics

This table reports the summary statistics of the major variables in the empirical analysis. Panel A lists the overall summary statistics. Panel B lists the averages of the climate change related variables by industry characterized by two-digit SIC code, where only the industries with at least five firms are shown. The sample is based on merging several databases including MSCI ESG STATS, NOAA Storm, USDA Crop Insurance, and COMPUSTAT, and covers the period between 1999 and 2012. Singleton firms at either the county or firm levels are deleted from the sample. Definitions for all the variables are in Appendix B. Size, Sales growth, ROA, Leverage, Dividend, Capexp, R&D, Adver, Cash, and Q have been winsorized at the 1st and 99th percentiles.

Panel A: Overall Summary Statistics

Variable	Observations	Mean	P25	Median	P75	Std
Climate rating	22,642	0.02	0	0	0	0.31
Climate strength	22,642	0.07	0	0	0	0.25
Climate concern	22,642	0.05	0	0	0	0.22
Net CER	22,642	0.00	0	0	0	0.12
Net CSR	22,642	-0.23	-0.50	-0.22	0	0.45
Raw disasters	22,642	23.31	9	19	33	17.44
Raw disasters (county-level data)	5,337	22.91	10	20	31	16.24
				Between-county std		14.24
				Within-county std		5.98
Disasters	22,642	0	-0.82	-0.25	0.56	1
Size (no logs, in $millions)	22,642	4,328.85	322.67	1,012.74	3,403.58	9,509.37
Size	22,642	6.96	5.78	6.92	8.13	1.75
Salesgrow	22,642	0.10	0	0.08	0.19	0.24
ROA	22,642	0.03	0.01	0.04	0.08	0.12
Leverage	22,642	0.22	0.04	0.19	0.33	0.20
Dividend	22,642	0.09	0	0.02	0.14	0.16
Capexp	22,642	0.05	0.01	0.03	0.06	0.05
R&D	22,642	0.03	0	0	0.03	0.07
Adver	22,642	0.01	0	0	0.01	0.03
Cash	22,642	0.17	0.03	0.09	0.23	0.19
Q	22,469	1.87	1.11	1.45	2.13	1.20

Panel B: Summary Statistics of Climate Rating by Industry

SIC2	Industry	Number of firms	Mean Climate strength	Mean Climate concern	Mean Climate rating
1	Agricultural production - crops	29	0.138	0	0.138
2	Agricultural production - livestock	9	0	0	0
7	Agricultural services	9	0	0	0
10	Metal mining	73	0.055	0	0.055
12	Coal mining	75	0.013	0.827	-0.813
13	Oil & gas extraction	819	0.096	0.354	-0.258
14	Nonmetallic minerals, except fuels	54	0.074	0	0.074
15	General building contractors	144	0.035	0	0.035
16	Heavy construction, except building	74	0.054	0.027	0.027
17	Special trade contractors	48	0.021	0	0.021
20	Food and kindred products	522	0.111	0.004	0.107
21	Tobacco products	44	0.182	0	0.182
22	Textile mill products	53	0.208	0	0.208
23	Apparel & other textile products	195	0	0	0
24	Lumber & wood products	114	0.061	0	0.061
25	Furniture & fixtures	173	0.116	0	0.116
26	Paper & allied products	258	0.147	0.004	0.143
27	Printing & publishing	311	0.019	0	0.019
28	Chemicals & allied products	1,784	0.089	0.003	0.086
29	Petroleum & coal products	152	0.217	0.671	-0.454
30	Rubber & miscellaneous plastics products	182	0.044	0	0.044

31	Leather & leather products	91	0.099	0	0.099
32	Stone, clay, & glass products	83	0.108	0	0.108
33	Primary metal industries	287	0.028	0.017	0.010
34	Fabricated metal products	276	0.054	0.004	0.051
35	Industrial machinery & equipment	1,244	0.071	0.083	-0.012
36	Electronic & other electric equipment	1599	0.061	0	0.061
37	Transportation equipment	560	0.086	0.236	-0.150
38	Instruments & related products	1,180	0.045	0.002	0.043
39	Miscellaneous manufacturing industries	153	0.046	0	0.046
40	Railroad transportation	82	0.098	0	0.098
41	Local & interurban passenger transit	12	0	0	0
42	Trucking & warehousing	158	0.101	0	0.101
44	Water transportation	108	0.037	0	0.037
45	Air transportation	161	0.118	0.056	0.062
47	Transportation services	91	0.044	0	0.044
48	Communications	670	0.040	0.004	0.036
49	Electric, gas & sanitary services	1,017	0.356	0.349	0.007
50	Wholesale trade – durable goods	392	0.005	0.008	-0.003
51	Wholesale trade – nondurable goods	225	0.053	0.036	0.018
52	Building materials & garden supplies	55	0.073	0	0.073
53	General merchandise stores	209	0.096	0	0.096
54	Food stores	138	0.087	0	0.087
55	Automotive dealers & service stations	169	0.012	0.426	-0.414
56	Apparel & accessory stores	354	0.020	0	0.020
57	Furniture & home furnishings store	106	0.028	0.009	0.019
58	Eating & drinking places	311	0.032	0	0.032
59	Miscellaneous retail	421	0.052	0	0.052
60	Depository institutions	1,962	0.017	0.001	0.017
61	Non-depository institutions	220	0.082	0.005	0.077
62	Security & commodity brokers	416	0.041	0.010	0.031
63	Insurance carriers	855	0.036	0.001	0.035
64	Insurance agents, brokers & service	117	0.026	0	0.026
65	Real estate	92	0.043	0	0.043
67	Holding & other investment offices	297	0	0	0
70	Hotels & other lodging places	59	0.102	0	0.102
72	Personal services	88	0.011	0	0.011
73	Business services	2,099	0.028	0.001	0.027
75	Auto repair, services, and parking	64	0.063	0.047	0.016
78	Motion pictures	74	0	0	0
79	Amusement & recreation services	120	0.017	0	0.017
80	Health services	343	0.006	0	0.006
81	Legal services	9	0	0	0
82	Education services	107	0.009	0	0.009
83	Social services	30	0	0	0
87	Engineering & management services	370	0.008	0	0.008
99	Non-operating establishments	40	0.250	0	0.250

Table 2. Natural Disasters and Climate Ratings (Linear Models)

This table reports the linear regression results to examine the effect of natural disasters on the ratings of firms' climate change policies. Panel A presents the *t*-test results on the difference between the climate ratings or firm de-meaned climate ratings of the firms located in counties with more natural disasters or more county de-meaned natural disasters, and those with fewer disasters or county de-meaned disasters matched by industry and firm size. Panel B reports the regression results of climate ratings on natural disasters. See Appendix B for the definitions of all the variables. All models also include the two-digit SIC industry and year dummies, and a constant term. Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: *t*-tests

	More Disasters	Fewer Disasters matched by industry and firm size	Difference
Observations	10,632	10,632	
Climate rating	0.007	0.010	-0.003
	More county de-meaned Disasters	Fewer county de-meaned Disasters matched by industry and firm size	
Observations	12,448	12,448	
Firm de-meaned Climate rating	0.003	-0.003	0.006***

Panel B: Regression Results

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Climate rating	Climate rating	Climate rating	Climate rating	Climate rating
Disasters	0.000	0.018***	0.017***	0.016***	0.014***
	(0.118)	(3.452)	(3.171)	(3.146)	(2.959)
Net CER			0.477***	0.460***	0.427***
			(8.985)	(8.901)	(9.436)
Net CSR			0.074***	0.075***	0.091***
			(7.708)	(8.489)	(9.793)
Size				0.034***	-0.041***
				(10.636)	(-4.436)
Salesgrow				0.002	0.026***
				(0.182)	(2.846)
ROA				-0.051**	0.035*
				(-2.255)	(1.698)
Leverage				-0.051***	0.023
				(-3.045)	(0.920)
Dividend				0.038**	-0.006
				(2.401)	(-0.434)
Capexp				0.066	-0.004
				(0.683)	(-0.038)
R&D				0.028	-0.035
				(0.527)	(-0.546)
Adver				-0.110	-0.136
				(-1.269)	(-0.747)
Cash				-0.011	-0.014
				(-0.726)	(-0.625)
Observations	22,642	22,642	22,642	22,642	22,642
Fixed county effects	No	Yes	Yes	Yes	Yes
Fixed firm effects	No	No	No	No	Yes
Adjusted R^2	0.13	0.20	0.24	0.26	0.52
Adjusted within R^2					0.16

Table 3. Natural Disasters and Climate Ratings (Probit Models)

This table reports the ordered-probit and probit regressions results to examine the effect of natural disasters on the ratings of firms' climate change policies. Model 1 uses ordered-probit model, and the other two models use probit models. See Appendix B for the definitions of all the variables. All models also include the two-digit SIC industry and year dummies, and a constant term. Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Dependent variable	Climate rating	Climate strength	Climate concern
Disasters	0.135***	0.194***	-0.155***
	(3.745)	(3.574)	(-2.614)
Net CER	1.931***		
	(7.756)		
CER net of Climate strength		1.330***	
		(6.580)	
CER net of Climate concern			-1.444**
			(-2.144)
Net CSR	0.333***	0.456***	-0.059
	(7.046)	(8.686)	(-0.646)
Size	0.190***	0.522***	0.407***
	(10.358)	(17.829)	(8.083)
Salesgrow	0.037	0.044	-0.178
	(0.646)	(0.425)	(-1.579)
ROA	-0.369**	-1.471***	-1.086**
	(-2.316)	(-5.597)	(-2.498)
Leverage	-0.331***	-0.352*	0.033
	(-2.903)	(-1.711)	(0.110)
Dividend	0.275***	0.568***	0.191
	(2.705)	(3.695)	(0.640)
Capexp	0.750	3.298***	2.823***
	(1.289)	(3.912)	(3.275)
R&D	0.153	-0.607	-12.307**
	(0.403)	(-0.778)	(-2.378)
Adver	-0.783	0.574	4.610*
	(-1.368)	(0.527)	(1.893)
Cash	-0.195*	0.550**	2.982***
	(-1.785)	(2.200)	(6.068)
Observations	22,642	22,642	22,642
Fixed county effects	Yes	Yes	Yes
Fixed firm effects	No	No	No
Pseudo R^2	0.33	0.51	0.69

Table 4. Asymmetric Effect of Natural Disasters on Climate Ratings

This table reports the linear regression results to examine an asymmetric effect of natural disasters on climate ratings conditional on whether there are more or fewer county de-meaned disasters. De-meaned X is the county and firm de-meaned variable X. See Appendix B for the definitions of all the X in the table. More county de-meaned Disasters is a dummy variable that equals one if the county de-meaned number of disasters is above the sample median, and zero otherwise, where the de-meaning is based on the county-level sample (keep only one observation for each county and year). Both models also include the two-digit SIC industry and year dummies, and a constant term. Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable	(1) De-meaned Climate rating	(2) De-meaned Climate rating
De-meaned Disasters	0.013***	0.003
	(2.897)	(0.422)
De-meaned Disasters * More county de-meaned Disasters		0.025***
		(2.939)
More county de-meaned Disasters		-0.004
		(-1.117)
De-meaned Net CER	0.518***	0.518***
	(11.469)	(11.449)
De-meaned Net CSR	0.076***	0.076***
	(7.860)	(7.870)
De-meaned Size	0.011	0.011
	(1.338)	(1.322)
De-meaned Salesgrow	-0.004	-0.004
	(-0.502)	(-0.511)
De-meaned ROA	-0.006	-0.005
	(-0.284)	(-0.271)
De-meaned Leverage	0.017	0.017
	(0.689)	(0.678)
De-meaned Dividend	0.010	0.009
	(0.692)	(0.656)
De-meaned Capexp	-0.120	-0.121
	(-1.303)	(-1.313)
De-meaned R&D	-0.007	-0.008
	(-0.103)	(-0.127)
De-meaned Adver	-0.166	-0.165
	(-0.900)	(-0.893)
De-meaned Cash	0.028	0.027
	(1.203)	(1.186)
Observations	22,642	22,642
Adjusted R^2	0.12	0.12

Table 5. Test of Belief Hypothesis

This table reports the results in testing the Belief Hypothesis, which states that experiencing extreme weather enhances beliefs in anthropogenic climate change and motivates managers to take climate-friendly corporate actions. Red state is a dummy variable that equals one if the headquarter state of a firm is leaning toward Republican Party in a given year, as indicated by more votes cast for the Republican candidate in the most recent presidential election, and zero otherwise. More male directors is a dummy variable that equals one if the percent of male directors of a firm in the previous year exceeds the sample median, and zero otherwise. Coastal county is a dummy variable that equals one if the headquarter of a firm is in a coastal county, and zero otherwise. Southern county is a dummy variable that equals one if the latitude of the headquarter of a firm is at or below the median latitude of all the headquarters of the firms in the sample, and zero otherwise. High population is a dummy variable that equals one if the population of the headquarter county of a firm is above the sample median, and zero otherwise. See Appendix B for the definitions of all other variables. All models also include the two-digit SIC industry and year dummies, and a constant term. Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Climate rating	Climate rating	Climate rating	Climate rating	Climate rating
Disasters * Red state	0.019**				
	(1.988)				
Red state	-0.026*				
	(-1.714)				
Disasters * More male directors		0.019**			
		(2.255)			
More male directors		0.009			
		(0.885)			
Disasters * Coastal county			0.023***		
			(2.604)		
Coastal county			0.025		
			(0.970)		
Disasters * Southern county				0.020**	
				(2.159)	
Southern county				-0.419***	
				(-3.371)	
Disasters * High population					0.017*
					(1.813)
High population					-0.345***
					(-3.770)
Disasters	0.007	0.009	0.004	0.003	0.004
	(1.313)	(1.123)	(0.551)	(0.421)	(0.563)
Net CER	0.427***	0.409***	0.426***	0.426***	0.427***
	(9.441)	(7.805)	(9.429)	(9.448)	(9.444)
Net CSR	0.091***	0.088***	0.091***	0.091***	0.091***
	(9.811)	(7.399)	(9.786)	(9.797)	(9.799)
Size	-0.041***	-0.066***	-0.041***	-0.041***	-0.041***
	(-4.375)	(-3.554)	(-4.442)	(-4.431)	(-4.440)
Salesgrow	0.025***	0.042**	0.025***	0.025***	0.025***
	(2.804)	(2.295)	(2.825)	(2.838)	(2.823)
ROA	0.036*	0.066*	0.035*	0.035*	0.036*
	(1.739)	(1.701)	(1.715)	(1.713)	(1.726)
Leverage	0.025	0.033	0.024	0.023	0.023
	(0.983)	(0.735)	(0.943)	(0.904)	(0.926)
Dividend	-0.006	0.014	-0.007	-0.006	-0.006
	(-0.443)	(0.494)	(-0.450)	(-0.434)	(-0.421)
Capexp	-0.004	0.237	-0.003	-0.005	-0.002

	(-0.043)	(1.533)	(-0.037)	(-0.050)	(-0.027)
R&D	-0.030	-0.144	-0.037	-0.037	-0.038
	(-0.466)	(-0.905)	(-0.577)	(-0.572)	(-0.591)
Adver	-0.135	-0.283	-0.132	-0.135	-0.135
	(-0.746)	(-0.935)	(-0.727)	(-0.743)	(-0.742)
Cash	-0.015	-0.029	-0.014	-0.015	-0.014
	(-0.683)	(-0.739)	(-0.627)	(-0.662)	(-0.637)
Observations	22,642	12,998	22,642	22,642	22,642
Fixed county effects	Yes	Yes	Yes	Yes	Yes
Fixed firm effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.52	0.54	0.52	0.52	0.52
Adjusted within R^2	0.16	0.21	0.16	0.16	0.16

Table 6. Test of Agency Cost Hypothesis

This table reports the results in testing the Agency Cost Hypothesis, which states that managers use the incidence of natural disasters as an excuse to take climate actions to advance their personal interests at the expense of shareholders. Large board is a dummy variable that equals one if the board size of a firm in the previous year is above the sample median, and zero otherwise. Classified board is a dummy variable that equals one if the board of a firm in the previous year is classified, and zero otherwise. Co-opted board is a dummy variable that equals one if the percent of non-executive directors in the previous year who were elected after the incumbent CEO took office is above the sample median, and zero otherwise. No ind blk is a dummy variable that equals one if there was no independent director on the board with at least 1% ownership in the previous year, and zero otherwise. Low leverage is a dummy variable that equals one if the debt ratio of a firm in the previous year is at or below the sample median, and zero otherwise. See Appendix B for the definitions of all other variables. All models also include the two-digit SIC industry and year dummies, and a constant term. Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Dependent variable	Climate rating	Climate rating	Climate rating	Climate rating	Climate rating
Disasters * Large board	-0.013				
	(-1.493)				
Large board	0.011				
	(1.000)				
Disasters * Classified board		0.027**			
		(2.331)			
Classified board		-0.071***			
		(-2.653)			
Disasters * Co-opted board			-0.003		
			(-0.362)		
Co-opted board			-0.005		
			(-0.419)		
Disasters * No ind blk				0.006	
				(0.748)	
No ind blk				-0.021**	
				(-2.181)	
Disasters * Low leverage					0.004
					(0.652)
Low leverage					-0.013
					(-1.479)
Disasters	0.026***	0.003	0.020**	0.014*	0.012**
	(3.494)	(0.300)	(2.466)	(1.796)	(1.981)
Net CER	0.409***	0.411***	0.414***	0.409***	0.426***
	(7.809)	(7.971)	(7.917)	(7.822)	(9.418)
Net CSR	0.088***	0.085***	0.087***	0.087***	0.091***
	(7.363)	(7.313)	(7.208)	(7.351)	(9.809)
Size	-0.067***	-0.059***	-0.069***	-0.065***	-0.042***
	(-3.615)	(-3.360)	(-3.616)	(-3.508)	(-4.466)
Salesgrow	0.043**	0.044**	0.047**	0.042**	0.026***
	(2.352)	(2.551)	(2.477)	(2.307)	(2.866)
ROA	0.068*	0.042	0.065	0.065*	0.035*
	(1.763)	(1.207)	(1.635)	(1.684)	(1.701)
Leverage	0.030	0.045	0.033	0.029	-0.002
	(0.665)	(1.146)	(0.724)	(0.648)	(-0.076)
Dividend	0.015	0.005	0.020	0.015	-0.007
	(0.521)	(0.190)	(0.677)	(0.529)	(-0.458)
Capexp	0.232	0.211	0.191	0.233	-0.001
	(1.495)	(1.427)	(1.178)	(1.499)	(-0.013)
R&D	-0.125	-0.103	-0.108	-0.142	-0.030

	(-0.789)	(-0.689)	(-0.643)	(-0.891)	(-0.460)
Adver	-0.279	-0.270	-0.318	-0.279	-0.135
	(-0.917)	(-0.964)	(-1.024)	(-0.916)	(-0.744)
Cash	-0.026	-0.018	-0.020	-0.027	-0.014
	(-0.664)	(-0.490)	(-0.491)	(-0.699)	(-0.605)
Observations	12,998	14,034	12,679	12,997	22,642
Fixed county effects	Yes	Yes	Yes	Yes	Yes
Fixed firm effects	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.54	0.53	0.55	0.54	0.52
Adjusted within R^2	0.21	0.20	0.21	0.21	0.16

Table 7. Test of Regulatory Risk Hypothesis

This table reports the results in testing the Regulatory Risk Hypothesis, which states that managers take climate actions in response to natural disasters to reduce the potential liabilities due to possible regulations as a result of the substantial damages associated with these disasters. Democrat pres is a dummy variable that equals one if the U.S. President is from the Democratic Party at a given year, and zero otherwise. High disaster loss is a dummy variable that equals one if the total loss incurred at the headquarter state of a firm in the previous year due to “mega-disasters” causing at least $1 billion damages is above the sample median, and zero otherwise. Post Deepwater is a dummy variable that equals one if the year is on or after 2010 when the Deepwater Horizon oil spill took place, and zero otherwise. High litigation risk is a dummy variable that equals one if the average climate concern of the industry of a firm in the previous year is above the sample median, and zero otherwise. See Appendix B for the definitions of all other variables. Models 1 & 3 also include the two-digit SIC industry dummies and a constant term. Models 2 & 4 also include the two-digit SIC industry and year dummies, and a constant term. Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	Climate rating	Climate rating	Climate rating	Climate rating
Disasters * Democrat pres	-0.008*			
	(-1.795)			
Democrat pres	0.071***			
	(13.369)			
Disasters * High disaster loss		-0.000		
		(-0.075)		
High disaster loss		-0.001		
		(-0.327)		
Disasters * Post Deepwater			-0.009	
			(-1.198)	
Post Deepwater			0.134***	
			(15.956)	
Disasters * High litigation risk				0.023
				(1.606)
High litigation risk				-0.070*
				(-1.721)
Disasters	0.004	0.014***	0.019***	0.007*
	(0.784)	(2.709)	(3.919)	(1.959)
Net CER	0.562***	0.427***	0.467***	0.435***
	(12.459)	(9.433)	(10.392)	(9.392)
Net CSR	0.065***	0.091***	0.083***	0.088***
	(6.887)	(9.785)	(8.919)	(9.431)
Size	0.026***	-0.041***	0.010	-0.040***
	(3.076)	(-4.429)	(1.238)	(-4.478)
Salesgrow	-0.018**	0.026***	0.006	0.026***
	(-2.100)	(2.845)	(0.660)	(2.871)
ROA	0.013	0.035*	-0.013	0.032
	(0.617)	(1.697)	(-0.650)	(1.549)
Leverage	-0.017	0.023	0.009	0.022
	(-0.674)	(0.919)	(0.358)	(0.904)
Dividend	0.015	-0.006	0.012	-0.009
	(1.008)	(-0.436)	(0.823)	(-0.651)
Capexp	-0.377***	-0.004	-0.099	-0.028
	(-4.030)	(-0.039)	(-1.059)	(-0.295)
R&D	-0.027	-0.035	-0.011	-0.034
	(-0.407)	(-0.539)	(-0.162)	(-0.536)
Adver	-0.307	-0.136	-0.129	-0.096
	(-1.526)	(-0.748)	(-0.669)	(-0.547)

Cash	0.082***	-0.014	0.043*	-0.017
	(3.321)	(-0.626)	(1.805)	(-0.787)
Observations	22,642	22,642	22,642	22,180
Fixed county effects	Yes	Yes	Yes	Yes
Fixed firm effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.49	0.52	0.51	0.52
Adjusted within R^2	0.11	0.16	0.14	0.16

Table 8. Climate Rating and Firm Performance

This table reports the results to examine the causal impact of climate ratings on firm performance as measured by Tobin's Q. Panel A reports the regression results based on different model specifications and samples. Panel B reports the *t*-tests for the difference between the change of Tobin's Q between 2009 and 2012 of the firms with positive "excess climate ratings at 2012" that also increased their climate ratings during this time period, and firms matched by industry and predicted value of climate rating at 2012 but experienced no change in climate ratings. The excess climate rating at 2012 is defined as the difference between the actual and the predicted value of climate rating at 2012 based on the regressions on the sample on or before 2009, using the specification in Model 5 of Panel B in Table 2. The results of Model 5 in Panel A are obtained by running the regressions of the change in Tobin's Q between 2009 and 2012 on the changes in the independent variables over the same time period over the matched sample in Panel B. For simplicity, the change sign "Δ" is omitted from the independent variables. See Appendix B for the definitions of all the variables. Models 1-4 of Panel A also include the two-digit SIC industry and year dummies, and a constant term. Model 5 also includes the two-digit SIC industry dummies and a constant term. Standard errors are adjusted for heteroscedasticity for all the models, and clustered at the firm level for Models 1-4. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Regression Results

Model	(1)	(2)	(3)	(4)	(5)
Sample	Full	Full	Full	Full	Firms matched by industry and predicted value of climate rating at 2012
Specification	OLS	FE	2SLS with FE		FD
			1st stage	2nd stage	
Dependent variable	Q	Q	Climate rating	Q	ΔQ
Climate rating	0.041*	-0.063**		1.293	0.005
	(1.722)	(-2.478)		(1.559)	(0.088)
Instrumental variables:					
Disasters			0.014***		
			(2.931)		
Red state			-0.029*		
			(-1.862)		
Control variables:					
Net CER	0.123	-0.149*	0.428***	-0.728*	-0.158
	(1.526)	(-1.702)	(9.508)	(-1.924)	(-1.165)
Net CSR	0.055**	-0.042*	0.091***	-0.166**	0.026
	(2.192)	(-1.835)	(9.818)	(-2.065)	(0.718)
Size	-0.037***	-0.354***	-0.041***	-0.297***	-0.044
	(-3.812)	(-9.061)	(-4.394)	(-5.601)	(-0.509)
Salesgrow	0.324***	0.230***	0.026***	0.195***	-0.034
	(6.397)	(6.475)	(2.848)	(4.524)	(-0.203)
ROA	2.119***	0.623***	0.036*	0.575***	-0.215
	(9.723)	(5.871)	(1.761)	(5.095)	(-1.196)
Leverage	0.104	-0.133	0.025	-0.165	-0.797**
	(1.094)	(-1.340)	(0.984)	(-1.532)	(-2.351)
Dividend	0.374***	-0.015	-0.007	-0.006	0.120
	(4.497)	(-0.309)	(-0.458)	(-0.117)	(0.632)
Capexp	2.200***	0.773***	-0.003	0.779***	0.288
	(7.260)	(3.013)	(-0.028)	(2.727)	(0.367)
R&D	5.061***	4.047***	-0.030	4.086***	5.244
	(12.299)	(6.771)	(-0.464)	(6.753)	(1.237)
Adver	3.873***	1.058	-0.128	1.252	2.880
	(4.588)	(0.917)	(-0.701)	(1.019)	(1.127)
Cash	1.609***	0.909***	-0.016	0.929***	-0.169

	(13.627)	(7.438)	(-0.694)	(7.338)	(-0.269)
Observations	22,469	22,469	22,469	22,469	346
Fixed county effects	No	Yes	Yes	Yes	No
Fixed firm effects	No	Yes	Yes	Yes	No
Hansen overidentification test				p-value=0.827	
Adjusted R^2	0.37	0.73	0.52		0.14
Adjusted within R^2		0.18	0.16		

Panel B: *t*-tests

	ΔClimate rating>0 and Excess climate rating at 2012>0	ΔClimate rating=0 matched by industry and predicted value of climate rating at 2012	Difference
Observations	173	173	
ΔClimate rating	1.023***	0	1.023***
ΔQ	0.029	0.050	-0.021

Table 9. Robustness Checks

This table reports the results to examine the robustness of the relationship between natural disasters and climate ratings. Billion disaster loss is the estimated total normalized state loss caused by "mega-disasters" in the previous year that resulted in at least $1 billion inflation-adjusted total economic damages. The allocation of state loss due to a given disaster is based on state GDPs. The normalization is based on state GDP at 2012. Climate change disasters is the total number of severe meteorological events in the previous year that are expected to increase with global warming with more certainty, including heat events, wildfires, droughts, and flooding. 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. See Appendix B for the definitions of all other variables. All models also include the two-digit SIC industry and year dummies, and a constant term. Standard errors are adjusted for heteroscedasticity and clustered at the firm level. *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)
Dependent variable	Climate rating	Climate rating	Climate rating
Billion disaster loss	0.001***		
	(2.626)		
Climate change disasters		0.007**	
		(2.090)	
Disasters			0.020***
			(3.775)
Ind norm net CER			0.101***
			(8.826)
Ind norm net CSR			0.163***
			(7.970)
Net CER	0.447***	0.427***	
	(9.815)	(9.440)	
Net CSR	0.092***	0.091***	
	(8.803)	(9.808)	
Size	-0.043***	-0.041***	-0.050***
	(-3.666)	(-4.444)	(-4.701)
Salesgrow	0.028**	0.026***	0.031***
	(2.520)	(2.845)	(3.098)
ROA	0.034	0.035*	0.026
	(1.351)	(1.697)	(1.093)
Leverage	0.009	0.023	0.041
	(0.321)	(0.903)	(1.343)
Dividend	-0.017	-0.007	-0.007
	(-0.996)	(-0.455)	(-0.429)
Capexp	-0.043	-0.006	-0.053
	(-0.385)	(-0.062)	(-0.509)
R&D	0.010	-0.034	-0.092
	(0.136)	(-0.528)	(-1.272)
Adver	-0.093	-0.142	-0.236
	(-0.505)	(-0.780)	(-0.951)
Cash	-0.022	-0.014	-0.006
	(-0.784)	(-0.607)	(-0.223)
Observations	16,815	22,641	18,980
Fixed state effects	Yes	No	No
Fixed county effects	No	Yes	Yes
Fixed firm effects	Yes	Yes	Yes
Adjusted R^2	0.51	0.52	0.51
Adjusted within R^2	0.15	0.16	0.13