Actions after Experiences: CEO Abnormal Climate Exposure and Corporate Carbon Reduction

Tianxi Wang [a], Angelica Gonzalez [a], Vathunyoo Sila [a]

Abstract

Using hand-collected CEO birthplace data of U.S. listed firms, we show that CEOs who are exposed to heightened abnormal climate trends exhibit a greater propensity to reduce corporate carbon emissions. Acknowledging the inherent long-term nature of climate change assessments, we use an innovative metric that takes into account a CEOs' formative years and their weather experiences to quantify this relationship. The effect is not driven by CEO disaster experiences or firm's exposure to climate change. With county-level data, we also verify our channel by showing people in areas more exposed to abnormal climate have stronger awareness towards climate change and are more likely to support carbon regulation. We find that CEO exposure to abnormal climate is a substitute for other factors that can promote carbon reduction, and the effect is unlikely an agency problem or greenwashing.

[a] The University of Edinburgh, 29 Buccleuch Place, Edinburgh EH8 9JS, UK.
Email address: t.wang-56@sms.ed.ac.uk
We thank Jiafu An, Yizhe Dong, Stephie Fried, Woon Sau Leung, Yue Liu, Jens Hagendorff, Wenxuan Hou, Nora Pankratz, Ruoran Zhao and seminar participants at the University of Edinburgh for their invaluable comments and suggestions.

1. Introduction and literature

Climate change has induced many problems in the world, and people are trying to mitigate the trend by reducing carbon emissions.

This paper examines whether personal exposure to abnormal climate can motivate CEOs to cut greenhouse gas (GHG) emissions and improve their firms' ESG performance. If stronger exposure can increase one's awareness on climate change, and stronger awareness can motivate CEOs to make greener decisions, this should be evident in corporate outcomes of firms managed by CEOs having stronger exposure compared with firms managed by CEOs having less exposure.

Using hand-collected data on 434 U.S. CEOs who managed 328 listed firms during the period 2003 to 2022, we find that CEOs cut carbon emissions in their firms when they witness an increase of abnormal climate in their hometowns compared with their childhood memories. The effect is robust to different measures of carbon emission and different measures of temperature variation[1]. We rule out several alternative explanations including the effect of disasters induced by climate change, the impact of firm headquarter exposure to climate change and CEO hometown bias. Moreover, we further explore the motivation of carbon reduction following CEOs' exposure to abnormal climate. Our analysis shows that the effect is more likely to be a substitute for other factors that facilitate carbon reduction and is not likely to be driven by economic considerations. More importantly, such carbon reduction is not at the cost of firm financial performance.

A key challenge in constructing a causal inference from CEO exposure to corporate outcomes is endogenous CEO-firm matching (see Fee, Hadlock and Pierce, 2013; Custódio and Metzger, 2014). In specific, if a CEO has a heightened exposure to climate change and that translates in increased awareness towards environmental concerns, the CEO might prefer to work in a firm with lower carbon emission; Further, if a firm has decided to improve its ESG performance and reduce carbon emission, it might look for a CEO with stronger awareness and more knowledge in climate change to implement

[1] There remains a debate as to how to measure corporate carbon emissions in empirical studies (see Aswani, Jitendra, Aneesh Raghunandan, and Shivaram Rajgopal, 2024, Are carbon emissions associated with stock returns?, *Review of Finance*, 28(1), pp.75-106). We use carbon intensity as our main carbon emission measure. It is defined as the total carbon emission scaled by firm total revenue. Our main results are robust when we use raw carbon emission.

its new strategy. In both cases, we are not able to conclude causality from CEO abnormal climate exposure to corporate carbon emission.

To address this problem, we develop a novel measure of CEO's abnormal climate exposure. This measure is constructed based on both a CEO's past experience and current experience during a CEO's tenure, which is not foreseeable for the firm when the CEO's appointment is made. Inspired by the abnormal temperature measure in Addoum, Ng and Ortiz-Bobea (2020), we measure a CEO's exposure to abnormal climate by the difference between a CEO's early-life extreme days and recent extreme days in the CEO's hometown. Specifically, we obtain daily gridded historical temperature data from the fifth generation of the European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global climate (ERA5). Then we count the number of extreme days defined by Addoum, Ng and Ortiz-Bobea (2020) during a CEO's formative years and her recent years of CEO tenure, and we obtain the difference of extreme days between the two periods. Our results are robust to several different measures based on temperature variation.

This measure has three unique advantages. First, it is relatively exogenous. Past experiences are observable. Focusing on CEO early-life can lead to CEO-firm endogenous matching. By contrast, even if a firm considers a CEO's early life experience or birthplace in recruitment, future abnormal climate in a CEO's hometown is not predictable, so our measure captures the exogenous variation of a CEO's exposure to abnormal climate. Second, by focusing on CEO's hometown climate, the measure is net of other corporate stakeholders (e.g., other employees, shareholders, regulators) and firm-level physical exposure to climate change (e.g., sea-level rise). Therefore, we isolate the pure effect of CEO abnormal climate change exposure on corporate carbon emission. Third, our measure has higher comparability because it is constructed based on a benchmark. Although on average, stronger exposure to abnormal climate will lead to stronger belief in climate change (Choi, Gao and Jiang, 2020; Sloggy et al., 2021), focusing on a single period will lead to bias. For example, if a CEO exposed to extreme temperature recently has no following reduction in carbon emission, it is possibly because she had similar or even stronger experience during her childhood, and as a result, she fails to form a perception of climate change given the recent high temperature. Therefore, our measure, taking past experience as a benchmark, captures the exogenous variation of CEO experiences.

One concern is that our results might be driven by a macro trend in climate change that affects all regions. If this is true, then what observed in CEO hometown might also happens in her firm's HQ. In our robustness checks, we include firm headquarter (HQ) abnormal climate exposure and run a horse race between firm HQ exposure and CEO hometown exposure. We find that CEO hometown abnormal climate exposure has a larger effect than firm HQ abnormal climate exposure and including firm HQ climate exposure does not eliminate the significance of CEO hometown climate exposure effect. Moreover, as some CEOs may prefer to work in hometown, which confounds our measure by reactions from stakeholders, we replicate our analysis after excluding CEOs working in their home counties and still have similar findings.

Another concern is that long-term climate change is usually accompanied by growing natural disasters including floods, droughts, storms (such as cyclones and hurricanes) and wildfires (Stott, Stone and Allen, 2004; Van Aalst, 2006; Kunreuther and Michel-Kerjan, 2007; Smith and Katz, 2013; Williams et al., 2019; Tschumi and Zscheischler, 2020). Differencing climate change from isolated natural disasters is important because mitigation strategies differ based on the nature of the event. For instance, a CEO who perceives the flooding of a plant as an outcome of uncontrollable, isolated events might opt to relocate the facility. Conversely, a CEO who identifies recurrent floods as indicative of climate change might prioritize strategies such as reducing carbon emissions alongside exploring new locations. Further, CEOs' early-life disaster experiences also affect their managerial styles (Bernile, Bhagwat and Rau, 2017). To mitigate this concern, we control for CEO early-life disaster experience from National Oceanic and Atmospheric Administration (NOAA) storm database and find our results still hold[2]. The results are also similar when CEOs with any fatal disaster experiences are excluded.

A key and implicit argument in our study is that CEOs are aware of hometown long-term temperature variation, and stronger perception can motivate them to cut corporate carbon emission. This argument is supported by many studies (e.g., O'Connor, Bard and Fisher, 1999; Krosnick et al., 2006; Leiserowitz, 2006; Brody et al., 2008; Howe et al., 2013). Besides, even if this argument is valid, it remains a question that whether our climate change variable measured by abnormal climate exposure

[2] The NOAA storm database (https://www.ncdc.noaa.gov/stormevents/) not only includes records on storms but also on all minds of disasters such as floods, droughts, tornados and hail etc.

is really perceived by people. To validate our climate change measure, we obtain the county-level survey data from Yale Climate Change Opinion Map and match our climate change measure to each county. We find that stronger exposure to abnormal climate will make local people more concerned with climate change, and these people are more likely to support carbon emission regulation.

In our further analysis, we show that the carbon reduction after stronger CEO climate change exposure may not be attributed to an agency problem. By contrast, a CEO's exposure can be a beneficial substitute for other green factors such as external public attention and the presence of an environmental committee, as the effect is only detectable when these factors are absent.

Moreover, we show three pieces of evidence that go against the agency problem interpretation. First, we find that this effect is driven by a CEO's personal preference, because the effect is amplified when the CEO is more powerful. The results are consistent when we measure a CEO's power in three different ways including retiring age, CEO-chair duality and relative compensation. Second, we fail to find any relationship between CEO climate change exposure and firm performance, indicating that this effect does not harm shareholder benefits. Third, we obtain ownership data from FactSet and use a textual analysis approach to identify each firm's green institutional shareholders by interpreting each shareholder's profile. We find no increase in green fund inflow following a CEO's climate change exposure, suggesting that the carbon reduction flowing a CEO's climate change exposure is not driven by such economic considerations.

Our study contributes to several strands of literature. First, it enriches our understanding in corporate outcomes of climate change. In terms of direct exposure to extreme weathers or disasters, Garel and Petit-Romec (2022) observe that after abnormally hot temperature around headquarters, firms tend to cut corporate carbon emissions. Huang et al., (2022) find that after disasters nearby, firms improve their ESG disclosure transparency, and firms with local institutional shareholders show more improvement. While these two studies look into the impact of climate on firm outcomes, our research stands apart in several distinct ways. We address the challenge of disentangling climate change from extreme weather events and disasters by utilizing a unique threshold: the childhood weather experiences of CEOs. This approach allows us to discern long-term climate change trends from short-term impacts related to extreme weather or disasters. Furthermore, our methodology focuses on the CEO's birthplace rather than relying on a firm's headquarters. This deliberate choice mitigates concerns regarding endogeneity, reducing potential biases associated with omitted variables at the firm level. Outcomes of climate and weather around a firm's headquarter cannot be attributed to a CEO's awareness, as it is not possible to isolate reactions of other stakeholders who are substantively affected (e.g., supply chain disruptions due to more frequently floods, lower working efficiency due to high temperature). Most significantly, we recognize the subjective nature of perceiving events as indicators of climate change. Individual experiences and characteristics shape these perceptions. By isolating the experiences of the most influential decision-maker within the firm—the CEO—we contend that we are better positioned to delineate between actions driven by climate change considerations and those stemming from disasters.

Second and more importantly, we also reveal personal abnormal climate change exposure as an increasingly important determinant of firm GHG emission and ESG performance. Gender (Homroy, 2022), institutional investors (Azar et al., 2021), environmental committees and board independence (Haque, 2017) are found to have impacts on firm ESG performance or GHG emissions. As many areas are increasingly exposed climate change, personal experience will also play an increasingly significant role in future corporate GHG emission.

Third, we contribute to CEO studies by revealing a dynamic interactive CEO effect of their past and recent experiences. Although finance literature is not new to updated expectations (e.g., analysts' forecasts are updated in terms of new information (Barron, Byard and Kim, 2002; Cotter, Tuna and Wysocki, 2006), firms' reaction to floods in each year is updated by accumulated floods during a period of time (Pankratz and Schiller, 2021)), updated expectations of CEOs are new to our specific research area. Previous studies have scrutinized the impacts of many CEO characteristics and life experiences on corporate outcomes. Many papers focus on CEOs' early-life experiences such as military experiences (Benmelech and Frydman, 2015), extreme natural disasters in formative years (Bernile, Bhagwat and Rau, 2017), life distress (Dittmar and Duchin, 2016) and famines (Feng and Johansson, 2018). Some studies also look into CEOs' later experiences such as recent extreme temperature exposure (Garel and Petit-Romec, 2022), working experiences (Custódio and Metzger, 2014) and innovative activities (Islam and Zein, 2020). Nguyen, Hagendorff and Eshraghi (2018) look further and investigate CEOs' cultural heritage transmitted from ancestors to following generations. We enrich this strand of literature by exploring updated CEO exposure to abnormal climate and by doing so highlight the interactive effect of CEOs' past and recent experiences, and also extend the literature of time-invariant CEO characteristics to a dynamic and time-variant view. More importantly, most previous studies focus on time-invariant characteristics, which are observable when the managers were recruited. By contrast, as abnormal climate in CEOs' hometowns is not reliably predictable, the change in CEO exposure is exogenous to firm characteristics. In this sense, by exploiting the time-variant CEO exposure, we largely mitigate the CEO-firm endogeneity problem.

Fourth, our study provides a clean measure of personal abnormal climate exposure. Our exposure measure is not based on limited significant disasters but long-term temperature variation. Therefore, the variation of this measure is net of other confounded factors and depends on future climate. In previous studies, Garel and Petit-Romec (2022) measure whether being exposed to abnormally hot temperatures in recent three years; Addoum, Ng and Ortiz-Bobea (2020) measure average temperature in each region over years; Giglio, et al. (2021) measure climate risk with flooding and sea level rise; and Correa et al. (2020) measure the exposure to several types of natural climate disasters. We distinguish from these papers by observing a long-term trend in climate change net of most confounded factors.

Finally, this paper also relates to studies of CEO hometown bias and preference. Managers may have advantages (e.g., better information) or have private benefits in hometowns (Jiang, Qian and Yonker, 2019), so CEOs may make biased decisions in hometown business. For example, managers tend to lend more in hometowns (Lim and Nguyen, 2021); mutual fund managers tend to invest more in firms located in the states where they were raised (Pool, Stoffman and Yonker, 2012); during industry downturn, managers are more reluctant to fire workers near their hometowns (Yonker, 2017); firms are also rated better by credit analysts born in the state of firm headquarters (Cornaggia, Cornaggia and Israelsen, 2020). Our results, however, show another channel. CEOs are also affected by what is happening in their hometowns as they observe and reflect through their hometown complex (Fischer et al., 1977; Low and Altman, 1992; Mesch and Manor, 1998; Hidalgo and Hernandez, 2001; Hernández et al., 2007). In this way, we also provide additional evidence showing that CEOs' characteristics associated with their hometowns persistently play a dynamic role in their managerial styles.

2. Hypothesis development

2.1 Public awareness on climate change

Many people are increasingly aware of climate change in recent years [3]. Studies have shown how long-term climate change can modify people's perceptions on global warming (Krosnick et al., 2006; Brody et al., 2008). In a study across 89 countries, Howe et al., (2013) find people perceive the recent temperature anomaly compared with the early period 1961 to 1990, and stronger anomaly predicts stronger perceptions. Similarly, higher outdoor temperature can raise local people's belief in global warming, and stronger belief raises people's willingness to pay to mitigate it (Joireman, Truelove and Duell, 2010). Besides, substantial proportions of people detect personally observable changes in climate, including seasons (36%), weather (25%), lake levels (24%), animals and plants (20%), and snowfall (19%) and these changes can be borne out in the climate record of NOAA climatic data and can predict people's perceptions of local climate change risk (Akerlof et al., 2013). They also argue that direct experience, vicarious experience and social construction all can contribute to people's perceptions on climate change.

2.2 Hometown complex

While people can move across locations, they generally have some attachments towards their hometown even if they no longer live there. People have "an affective bond" with specific areas where they like to stay and where they feel comfortable (Fischer et al., 1977; Low and Altman, 1992; Hidalgo and Hernandez, 2001). Meanwhile, by interacting with certain places, people can feel a sense of belonging to a specific place (Hernández et al., 2007). Such bonds are stronger for areas where friends and family members live (Mesch and Manor, 1998) and for those native to the place (Hernández et al., 2007).

People are likely to have continuous access to the information in their hometowns because of family members or old friends living there (Lim and Nguyen, 2021). Birthplaces of current political leaders

---

[3] News media have noticed that many people are sensitive to significant climate change. For example, many people suffered from the record-breaking temperature in recent summers in London (Climate change: Summer 2022 smashed dozens of UK records - BBC News); people also notice that recent winters are warmer than before (Unusual winter warmth will cap the warmest year on record for parts of Europe - The Washington Post); people also miss Christmas and winters full of snow (How many White Christmases has your city had? See holiday snow history. - Washington Post) while the lack of snow prevents people from classic winters sports (D.C., Philly and New York have seen no snow this winter. What's going on? - The Washington Post).

are better developed (Hodler and Raschky, 2014); mutual fund managers tend to invest more in firms located in the states where they were raised (Pool, Stoffman and Yonker, 2012); during industry downturn, managers are more reluctant to fire workers near their hometowns (Yonker, 2017) and firms are also rated better by credit analysts born in the state of firm headquarters (Cornaggia, Cornaggia and Israelsen, 2020). Our climate change measure exploits this hometown complex. We argue that people update their expectations on climate change given that they can easily keep up with new climate events and damage caused in their hometowns through family and friends or, alternatively, can obtain first-hand information whilst spending time in their hometown regularly. Further, this information is salient as they are likely to be attached to places and people.

2.3 Climate change: from experiences to actions

People react to climate change for economic reasons. In financial markets, investors are concerned about climate risk and carbon risk (Krueger, Sautner and Starks, 2020; Hong, Karolyi and Scheinkman, 2020; Bolton and Kacperczyk, 2021), and both regulatory and physical impacts of climate change are considered (Giglio et al., 2021). Investors value climate risk disclosure (Ilhan et al., 2021), and risks related to climate change are also priced in the option market (Ilhan et al., 2021), bond market (Huynh and Xia,2021) and mortgage market (Giglio et al., 2021; Nguyen et al., 2022). On firm level, customers replace suppliers that are more exposed to extreme temperature and floods (Pankratz and Schiller, 2021).

Apart from perceived or realized physical risks, people's awareness of climate change also leads to heterogeneous reactions. Baldauf, Garlappi and Yannelis (2020) find that climate change particularly has an effect on real estate prices when sellers have a belief in climate change. Moreover, fund managers located in major disaster regions tend to underweight the stocks in disaster zones (Alok, Kumar and Wermers, 2020). Bernstein et al. (2022) reveal that in the US, republicans are more likely to own houses exposed to higher sea level rise.

People become more environment-friendly when their awareness of climate change increases (O'Connor, Bard and Fisher, 1999; Leiserowitz, 2006). Among those who are concerned about climate change, 43% reduce energy use at home, 39% reduce gasoline consumption and 26% engaged in other behaviours such as increasing recycling (Semenza et al., 2008). Floods also raise public concerns on climate change and people having flood experience are more confident that their actions will contribute to mitigating climate change (Spence et al., 2011).

Given above literature, we hypothesize that CEOs exposed to abnormal climate in their hometowns compared to their formative period memories, raise their awareness on climate change. As a result, these CEOs will pay more attention to green development and make efforts for better ESG performance and lower carbon emission.

3. Sample and variables

3.1 Sample construction and dependent variables

We start from Refinitiv database for carbon emission and ESG performance variables. Our initial sample with non-missing values in carbon emission comprises 6,955 firm-year observations from 1,065 US listed firms managed by 1,784 CEOs during 2003 to 2022. These firms are incorporated in the US and are listed in a US stock exchange. We follow Shapiro (2021) and construct our main carbon emission measure using emission intensity, which is the total carbon emission over firm total revenue. We also use the total carbon emission as an alternative measure in a robustness check.

Then we extract CEO data from BoradEx and US Executive Compensation database (Execucomp). We merge the two datasets and hand collect CEO names if they are missing in databases. As our climate measure is based on CEO hometown, we follow Bernile, Bhagwat and Rau (2017) and search for CEO birthplace information from their biographical data from the official company website and US Executive Compensation database. We search on Google in the last instance.

We are able to identify the birthplace information of 669 CEOs. After excluding foreign CEOs, we end up with 434 CEOs having county-level birthplace information. They come from 221 counties all over the US. We require granular county-level birthplace information because many states are very large and the within-state climate variation can be drastic. The final sample consists of 2,363 firm-year observations from 325 listed firm managed by these 434 CEOs during 2003 to 2022. The step-by-step sample construction can be found in Table A2, and the detailed CEO distribution is illustrated in Figure 1. The birthplaces of CEOs are concentrated in three areas (the area around New York, the Great Lakes region, and California) while also have a good representation across the US. Our sample coverage on

US CEO county-level birthplace in percentage is comparable to previous papers. Among the 1,784 CEOs having firm-year observations with non-missing values of variables, we identify around 24.3% of their birthplace information in our final sample while the percentage for Bernile, Bhagwat and Rau (2017) is 22.1% (1,508 out of 6,804 US CEO birthplace). Firm financial variables are obtained from Refinitiv and are complemented with Compustat. The carbon emission data (in tons) and ESG rating data are from Refinitiv.

3.2 Measuring abnormal climate exposure: independent variables

We follow Addoum, Ng and Ortiz-Bobea (2020) and Pankratz and Schiller (2021) and obtain the daily gridded historical temperature data from the fifth generation of the European Centre for Medium-Range Weather Forecasts (ECMWF) atmospheric reanalysis of the global climate (ERA5). It covers historical temperature data since 1940. The database includes gridded hourly surface temperature and precipitation data all over the US. The grid resolution for temperature is 0.5° (longitude) ×0.5° (latitude). We obtain the maximum, minimum and average temperature for each grid-day, and then calculate the three measures for each county-day using the average of all grids in each county.

To measure a CEO's exposure to abnormal climate, we follow Choi, Gao and Jiang (2020) and construct a measure that captures the difference in days of extreme temperature between that prevalent during a CEO's formative year experience and that during her recent experience. Following Nelson (1993) and Bernile, Bhagwat and Rau (2017), we set the childhood years or formative years as the benchmark period during which a CEO was 5-15 years old. We then count the number of extreme days. Following Addoum, Ng and Ortiz-Bobea (2020) we define an extremely hot day as a day of which the highest temperature is above 30℃ and an extremely cold day as a day of which the lowest temperature is below 0℃. With the number of hot and cold days in each month, we follow Choi, Gao and Jiang (2020) and decompose the perceived abnormal extreme days in county i and in month τ of the current year T into three components.

$$Ab\_Day_{i,t,\tau} = Day_{i,t,\tau} - (Aver\_Day_{i,T} + Mon\_Day_{i,T,\tau})$$

where $Ab\_Day_{i,t,\tau}$ is the perceived abnormal extreme days for each CEO based on the comparison of the CEO's formative year hometown extreme days and recent hometown extreme days in month τ

of year t. $Day_{i,t,\tau}$ is the real number of extreme days in month τ of year t. For a CEO born in year $T-5$, $Aver\_Day_{i,T}$ is the average monthly number of extreme days in a CEO's county of birth i over the 120 months (10 years) during the CEO's formative years (T to $T+9$). $Mon\_Day_{i,T,\tau}$ is the average deviation of month τ's value from the overall decade average. In specific, $Mon\_Temp_{i,T,\tau}$ is the average extreme days in county i in the same calendar month τ over the 10-year formative period minus $Aver\_Day_{i,T}$. For a CEO in month τ, $Ab\_Day_{i,t,\tau}$ is the difference between the expected hometown extreme days based on their childhood memory and current hometown extreme days. It measures the unexpected and excessive extreme days compared with CEOs' early-year benchmarks. After obtaining $Ab\_Day_{i,t,\tau}$ for each month and each county, we annualize the measure by adding up its monthly abnormal extreme days $Ab\_Day_{i,t}$ for each year. [4]

As we end up with annualized abnormal temperature, Choi, Gao and Jiang (2020)'s decomposition of abnormal temperature above can be simplified as

$$Ab\_Day_{i,t} = Day_{i,t} - Aver\_Day_{i,T}$$

where $Ab\_Day_{i,t}$ is the annual average abnormal extreme days in year t, $Day_{i,t}$ is the annual average extreme days in year t, $Aver\_Day_{i,T}$ is the annual average extreme days of T to $T+9$, and the CEO was born in year $T-5$. Intuitively, $Ab\_Day_{i,t}$ is simply the difference between the current hometown extreme days and the formative period hometown extreme days.[5] We count the abnormally hot days,

[4] For example, for a CEO born in 1960, her abnormal climate exposure in 2013 ins constructed as follows. First, we count the number of extreme days during the decade of 1965-1974 in her hometown for each month. Then we obtain the average of each month over the 10 years. In this example, assume the average number of extreme days in the ten Januarys is 13, and the figure for the ten Februarys, Marchs, Aprils, Mays, Junes, Julys, Augusts, Septembers, Octobers, Novembers, Decembers are 11, 15, 16, 18, 19, 20, 22, 28, 18, 11, 9, respectively. And for 2013, the numbers of extreme days for each month from January to December in her hometown are 15, 16, 11, 13, 16, 17, 29, 30, 28, 17, 20, 21, then for January, $Day_{i,t,1}$=15, $Aver\_Day_{i,T}$= (13+11+15+16+18+19+20+22+28+18+11+9)/12=16.67, $Mon\_Day_{i,T,1}$= 13-$Aver\_Day_{i,T}$=13-16.67=-3.37. Then we obtain $Mon\_Day_{i,T,\tau}$ for τ=2, 3, 4, 5, 6, 7, 8, 9, 10, 11 and 12, respectively. Finally, the abnormal climate exposure for this CEO in 2013 is equal to the average value of all the 12 months, that is, $\sum_{i=1}^{12} Mon\_Day_{i,T,\tau}$.

[5] Let $X_{Y,\tau}$ denote the number of extreme days in a CEO's birth county in month τ of year Y , for a CEO born in year $T-5$, Y is from T to $T+9$ and τ is from 1 to 12. For a CEO's formative years, we have numbers of extreme days for 120 months. For each January ($\tau=1$), we can obtain the average number of extreme days of the same month during the decade of T to $T+9$, which is $\overline{X_{Y,1}}$=($\sum_{Y=T}^{T+9} X_{Y,1}$)/10. In this way, we also have $\overline{X_{Y,2}}$, $\overline{X_{Y,2}}$, …, $\overline{X_{Y,12}}$ for other months. For the current year t (e.g., 2016) of a firm, the number of extreme days for month τ is $X_{t,\tau}$. For January ($\tau=1$), $Ab\_Day_{t,1}$=$X_{t,1}$-$\overline{X_{Y,1}}$, in the similar way, we also have $Ab\_Day_{t,2}$,

cold days and the sum of both types of days respectively to develop three measures for CEO abnormal climate exposure.

For robustness checks, we obtain other measures of extreme temperature variation from The National Oceanic and Atmospheric Administration (NOAA). We draw monthly county-level data and compute maximum, minimum and average temperatures, and develop three measures similar to the extreme day measures above by replacing extreme days with temperature values.

3.3 Baseline specification and control variables

With the measure of abnormal extreme days in CEO birthplaces, we develop our baseline regression as follows.

$$Y_{i,t} = \beta\, Ab\_Day_{i,t} + \gamma' \mathbf{X} + \theta_t + \theta_j + \theta_s$$

Where $Y_{i,t}$ is the outcome variable (e.g., carbon emission) for firm i in year t, $\mathbf{X}$ is a set of control variables, θ_t denotes year fixed effects, θ_j denotes GICS industry fixed effects, and θ_s denotes CEO birthplace fixed effects. We control for CEO birth state fixed effects because many counties only supply one CEO in our sample, but the baseline results still hold with county-level fixed effects. We do not control for firm fixed effects as there is little within-firm CEO variation in our sample.

Following Azar et al., (2021), we control for a set of control variables. We include firm size (logarithm of total assets) to control for potential public pressure on environment protection and the scale of firm business activity; we include book to market ratio to control for firm growth opportunity; we also include a measure for performance, ROA (earnings before interest, taxes, depreciation and amortization to total assets); we then include PPE (tangibility, fixed assets to total assets) and leverage

---

$Ab\_Day_{t,3}$, …, $Ab\_Day_{t,12}$. The total number of extreme days in the current year t is the sum of $Ab\_Day_{t,\tau}$, which is $\sum_{\tau=1}^{12} Ab\_Day_{t,\tau}$, and this is equal to $\sum_{\tau=1}^{12}(X_{t,\tau} - \overline{X_{Y,\tau}}) = \sum_{\tau=1}^{12} X_{t,\tau} - \sum_{\tau=1}^{12} \overline{X_{Y,\tau}} = Day_t$-$(\sum_{\tau=1}^{12} \sum_{Y=T}^{T+9} X_{Y,\tau})/10 = Day_t - (X_{T,1} + X_{T,2} + \cdots + X_{T,12} + X_{T+1,1} + X_{T+,2} + \cdots + X_{T+1,12} + \cdots + X_{T+9,1} + \cdots + X_{T+9,12})/10 = Day_t - Aver\_Day_T$, where Day_t is the total number of extreme days in the current year t and $Aver\_Day_T$ is the yearly average of extreme days over the formative of the CEO from T to $T+9$. The simplification indicates that the above calculation can be illustrated in an easier way using the same example. For a CEO born in 1960, we count the total number of extreme days in her hometown during 1965-1974, which is (13+11+15+16+18+19+20+22+28+18+11+9) × 10=2000, and the average of each year during 1965-1974 is 2000/10=200, which is $Aver\_Day_{i,T}$. $Day_{i,t}$ is the total number of extreme days in 2013, which is 15+16+11+13+16+17+29+30+28+17+20+21=233, then her abnormal climate experience is measured as 233-200=33 days.

(the sum of long-term and short-term debt over total assets), because these variable measures credit and financial constraints of a firm. Higher leverage makes a firm more financially constrained and have fewer resources for environmental issues while more tangible assets can support more borrowings. As we focus on characteristics of CEOs, we follow Bernile, Bhagwat and Rau (2017) and further control for logarithm of CEO age and CEO gender (a dummy equal to one for male and zero otherwise).

3.4 Variables used in the validation test

In our channel test, we obtain county-level survey data on people's opinions on climate change from Yale Climate Change Map. County-level socio-economic data (including education level, unemployment rate and GDP) are from US Bureau of Economic Analysis, US Department of Agriculture, U.S. Department of Labor and Bureau of Labor Statistics.

3.5 Summary statistics

In Table 1, we present the summary statistics of climate variables, firm and CEO variables, and county-level variables in panels A, B, C, respectively. The baseline sample has 2,260 firm-year observations while there can be a few missing values for certain variables. In line with the overall trend of global warming, the numbers of abnormal extreme days and abnormal hot days are positive, and the sample abnormal temperature is also positive. By contrast, the number of abnormal cold days is negative.

Figure 2 displays the geographical distribution of the increase of the average of annual hot days with the comparison of two periods, each one composed of two decades; (i.e., 1945-1964 vs 2002-2021).Importantly, we note a variation on the extent of annual average hot day increases across regions in the USA. Whilst some places have small increases (e.g., some places in the north east), in some areas of Florida, the surge has been notable, with an increase of up to 50 days. More specifically, in those areas, there are 50 more days with extremely hot temperatures in a year during 2012-2021 than during 1945-1964. Figure 3 displays variation across regions and an increase in the number of hot days in four different decades of 1945-1954, 1955-1964, 2002-2011 and 2012-2021, showing that the number of extreme days in most areas in the US over time.

4. Results

4.1 CEO abnormal climate exposure and carbon emission

Table 2 presents the results of our baseline regressions. The outcome variable is carbon emission intensity, which is corporate total carbon emission divided by revenue. We have three baseline independent variables: the number of abnormal extreme days, the number of abnormal hot days, and the number of abnormal cold days. Columns (1), (3) and (5) include firm fixed effects while Columns (2), (4) and (6) include industry fixed effects. Our results in Columns (1) and (2) show that one additional abnormal day of extreme temperature in a month (or 12 days in a year) in a CEO's hometown can lead to a reduction of 40 to 71 grams of CO2 for each dollar of revenue. The effect is economically significant as the sample mean of emission intensity is 510 grams.

We find a negative and significant correlation between firm size and emission intensity. This may reflect the economies of scale, as large firms tend to have a lower marginal emission level for each unit increase in revenue. Interestingly, we do not find a significant effect of firm tangibility, i.e., PPE, on emission intensity, as found in Iovino, Martin and Sauvagnat (2021). CEO age and gender seem not to play a role here either. The results of other control variables are consistent with Azar et al. (2021).

By comparing the results of our three different measures, we find that CEOs are sensitive to both growing hot days and cold days, but the coefficients of cold days are only marginally significant. Although current climate change is usually described as global warming, it is accompanied by both extremely hot and cold weathers. The results are consistent with Capstick and Pidgeon (2014), where they show although some people consider extremely cold weather as a signal against climate change, most people will see it as pointing towards the reality of climate change.

4.2 Robustness checks

4.2.1 Alternative measures of abnormal climate exposure

For robustness, we first check our results are not sensitive to how we measure exposure to abnormal climate . Instead of counting the number of abnormal days, we apply three alternative measures of abnormal climate exposure based on the maximum, average and minimum temperatures. The construction of these alternative measures is similar to that of our baseline measures. We first calculate the highest, average and lowest temperatures during a month for each county and annualize the values. Then we obtain the difference between the decade-average value during a CEO's formative years and the value for the current year in her birth county.

Consistent with our baseline results, Table 3 shows similar indications. A rise of one Celsius degree in the annual maximum temperature can lead to 53 grams decrease of carbon emissions for every dollar of revenue, which is over 9% of the sample mean.

4.2.2 Absolute measure of carbon emission

As argued by Aswani, Raghunandan and Rajgopal (2024), in many relevant studies, the empirical results are sensitive to different forms of carbon emissions (raw values and scaled values). In this robustness check, we use the raw values of carbon emissions rather than a ratio as in our baseline results. The unit of CO_2 emission is one million tonnes. In Table 4, we show that one more abnormal extreme day in CEO experiences leads to 1.7 million tonnes reduction of carbon emission, which is around 20% of the sample mean and 7% of the sample standard deviation. The results make similar economic sense to those of our baseline results.

4.2.3 Ruling out firm headquarter abnormal climate exposure: a horserace between hometown and headquarter abnormal climate exposure and a placebo test

We focus CEO hometowns to isolate the impacts of firm-level climate-driven omitted variables. However, one might still argue that climate change is a global trend, so a firm's headquarter and its CEO's birth county might have similar abnormal climate exposure in the same year. If this was the case, then our measure would fail to capture CEOs' exposure net of other confounders, because some firm-level omitted factors can be affected by the common climate trend while also drive corporate outcomes. For example, if stakeholders (i.e., shareholders, regulators, other managers local public etc) all have similar exposure to abnormal climate, or if a firm's business also suffers substantive loss from abnormal climate in headquarters, we will fail to conclude it is CEO perceptions that reduce carbon emission. To rule out the potential impacts of a common climate trend that affect both CEO hometowns and firm headquarters, we construct a similar abnormal climate measure for each firm's headquarter. In specific, we obtain the difference between the current extreme days and average extreme days in the past decade for each firm's headquarter.

We find that the correlation between HQ abnormal extreme days and CEO hometown abnormal extreme days is only around 0.3, suggesting an absence of a common trend that drives abnormal climate in both places. In addition, in columns (1)-(3) of Table 5, we include this headquarter climate measure in our baseline regressions in Table 5. The results of CEO birthplace climate variables are similar while headquarter climate change seems not to have a significant impact on corporate carbon emission. In columns (4)-(6), we conduct a placebo test which excludes CEO hometown climate change variables and only keeps firm headquarter climate change variables. If our results are driven by some unobserved common trends, we should observe similar coefficients on firm headquarter climate change variables. Unsurprisingly, the insignificance of these coefficients provides us more confidence on our conjecture.

Another concern about hometown is that if some CEOs work near their hometowns, their firms and their hometowns would have similar exposure to abnormal climate. This overlap may drive the results. In an unreported table, we replicate our regressions by excluding CEOs working in their home counties and the results still hold.

4.2.4 Ruling out disaster effects

CEO early-life disaster experiences can affect corporate outcomes such as risk (Bernile, Bhagwat and Rau, 2017) and corporate social responsibility performance (O'Sullivan, Zolotoy and Fan, 2021). One challenge to our identification is that climate change may also induce more natural disasters such as floods, wild fires and hurricanes. If so, the results may actually be attributed to CEO disaster experiences. To rule out this explanation, we include a disaster variable in our baseline regressions.

We draw climate disaster records data from NOAA's Storm Events Database. It provides all types of county-level disaster records including floods, hurricanes, hot wave, heavy snow, wildfires, volcano eruptions etc. It also provides financial and life loss in each disaster. The data period starts from 1950 so we lose a few observations in our sample as some CEOs were born before that. Following Bernile, Bhagwat and Rau (2017), we first count the number of fatal disasters in each county-year and calculate its decade-average during a CEO's formative years. We then construct a similar variable to measure a

CEO's abnormal hometown disaster experiences by obtaining the difference between the numbers of fatal disasters of the current year and the decade-average in the CEO's formative years. We include CEO early-life disasters and abnormal disasters in our baseline regressions respectively. The results are very similar to the baseline results.

The correlation between our abnormal extreme days measure and the abnormal disasters is close to zero (-0.03), indicating that our abnormal climate exposure measure is not driven by disasters. Moreover, in Table 6, we include CEO early-life disaster experiences in columns (1), (3) and (5), and in the rest of the columns we include abnormal disaster experiences. Most of our results are qualitatively similar although the abnormal cold day measure loses its significance. In unreported result we also find that the results hold if we only focus on CEOs who have experienced no more disasters in the current year than the average disasters in their formative years (abnormal disaster is lower than zero). If our results are driven by a disaster effect, then experiencing fewer disasters should not motivate these CEOs to cut carbon emission.

4.3 Validating the Channel

Our study is grounded in the premise that individuals exposed to sustained changes in climate are more inclined to believe in climate change, and our abnormal climate exposure measure can properly capture people's experiences in climate trend. (Krosnick et al., 2006; Brody et al., 2008). A deeper impression on the long-term trend of climate can boost a person's awareness towards climate change (Howe et al., 2013; Capstick and Pidgeon, 2014). Such awareness can further motivate a person to be more environment-friendly (Joireman, Truelove and Duell, 2010).

To verify that our abnormal climate measure can capture people's exposure, and also this exposure can raise people's awareness to climate change, we collect survey data from Yale Climate Opinion Maps. The dataset contains county-level public opinions towards climate change in certain years. We extract the outcomes of three highly relevant survey questions: (1) Do you often discuss global warming with your friends and family?; (2) Do you agree that global warming is affecting the weather in the United States?; (3) How much do you support or oppose to regulate carbon dioxide (the primary greenhouse gas) as a pollutant? We then construct similar measures of abnormal extreme days and abnormal hot days to the CEO abnormal climate exposure measures by calculating the difference between the current year and the average of a certain decade some years ago. The survey outcomes are available for 2018-2021 for survey question (1), 2016 and 2018-2021 for question (2), and 2014, 2016 and 2018-2021 for question (3).

We test whether our measures, county-level abnormal days of extreme temperatures and hot temperatures, can predict local people's opinions on climate change. We run the following regression.

$$Y_{i,t} = \beta\ Ab\_Temp_{i,t,d} + \gamma' \mathbf{X} + \theta_t + \theta_c$$

Where $Y_{i,t}$ is the percent of interviewed people that have a positive response to each survey question in county i and year t. $Ab\_Temp_{i,t}$ is either the number of abnormal extreme days or abnormal hot days. **X** is a vector of control variables. As indicated in Kahn and Kotchen (2011), Akerlof et al. (2013) and Sloggy et al. (2021), demographic characteristics such as education, economic development and unemployment have significant impacts on people's opinions on climate change, therefore, in **X** we control for local unemployment rate, percentage of local people having a Bachelor's degree, and log of local GDP. θ_t and θ_c are year and county fixed effects.[6] The standard errors are clustered on county level.

Table 7 presents the results based on the decade that is 20 years apart from the current year. For example, for a county in 2015, we calculate its average annual extreme days during 1995-2004, and then subtract the value from its annual extreme days in 2015. In general, for a county in year t, we calculate its average annual extreme days during $t-20$ to $t-11$, and then obtain the difference between the extreme days of year t and the decade-average as the abnormal extreme days of this county in year t.

Columns (1)-(3) use the abnormal extreme days and columns (4)-(6) use the abnormal hot days. The variable Bachelor's degree is omitted in columns (2) and (5) because the county-level education data is not updated every year and there is no variation for this variable during 2018-2021. The results show that our measures can predict people's awareness on climate change. People exposed to more

[6] The results still hold if we further control for population increase rate and replace logarithm of GDP with GDP per capita.

abnormal extreme days and hot days discuss climate change more with others, believe that the trend is affecting the weather, and believe CO2 emission should be regulated as a pollutant.

In Figures 4 and 5, we plot the coefficients and their confidence intervals of different opinion variables and different time spans of abnormal climate measures. The values on the horizontal axis denote how many years the selected decade is apart from the current year. We display the results year by year. For a county in year t, we calculate the decade average in $(t-10, t-1)$, $(t-11, t-2)$, $(t-12, t-3)$, $(t-13, t-4)\ldots$ $(t-61, t-50)$, and then construct an abnormal climate change variable for each combination of a climate measure and a time span. Apart from a few exceptions, almost all the coefficients of different time spans are significant and positive.

4.4 Further analysis: motivation of the exposure-induced carbon emission reduction

Our results show a significant carbon emission reduction when a CEO is exposed to abnormal climate in her hometown. However, this reduction might be de facto an agency problem (e.g., Bénabou and Tirole, 2010; Krüger, 2015; Masulis and Reza, 2015) or, alternatively, it can be beneficial to the firm (e.g., Dhaliwal et al., 2011; Deng, Kang and Low, 2013). We explore this question by studying the heterogeneity of firms of different characteristics.

4.4.1 Information environment: analyst following and inclusion of MSCI climate index

Previous studies show that the number of analysts following a firm are associated with firm ESG performance. On the one hand, analyst coverage improves information environment and mitigates agency problems in corporate ESG, which reduces greenwashing (Adhikari, 2016). On the other hand, pressure from analysts also drives corporate myopia in ESG (Qian, Lu and Yu, 2019). We first explore the heterogenous roles of CEO abnormal climate exposure in carbon reduction among firms with different levels of analyst coverage.

We count the number of analysts covering a firm in each year, and then split our sample into high-analyst group and low-analyst group based on the median number of analysts. The cut-off point is 20 analysts. We replicate our baseline regressions in the two sub-groups, respectively. The results are summarized in Table 8. We find that, the carbon reduction effect of CEO's abnormal climate change exposure only exists when a firm is less exposed to analyst coverage.

We then conduct a similar sub-sample test for the inclusion of MSCI global climate change index. Following Azar et al. (2021), we classify each firm-year observation according to whether it is included in the MSCI index. Instead of the MSCI World Index, we use the more specialised MSCI Global Climate Change Index, which is specific for firms that are more exposed to climate change. The intuition is that, firms included in the index attract more public attention (Boone and White, 2015), so that they also receive more pressure on carbon emission. Table 9 presents the results. We find that, the effect of CEO abnormal climate exposure only exists when the firm is not included by the MSCI climate change index. If the firm is included in the MSCI climate change index, then CEO exposure does not play a role in corporate carbon reduction.

Overall, the results in Table 8 and Table 9 indicate that CEO abnormal climate exposure only decreases carbon emission in firms that lack external attention. The results have two possible explanations. First, if analyst following and MSCI inclusion inhibit firms' long-term carbon reduction campaigns and drive firms to focus on some superficial progress, consistent with Qian, Lu and Yu (2019), the lack of external attention motivates CEOs to further reduce carbon emission as there is less pressure for short-term performance. Second, in line with Adhikari (2016), if more external attention can improve information environment and discourage firms from greenwashing and spend more on substantive carbon reduction, then CEO abnormal climate exposure can be a substitute for external attention in carbon reduction when such attention is absent. We will further explore which explanation is more dominant together with other evidence in the following sections.

4.4.2 Environmental committee

It has been shown that the environmental committee increases corporate GHG disclosure (Liao, Luo and Tang, 2015), thus impulses pressure on firm carbon emission performance. We classify firms by the presence of environmental committee. In the sub-sample tests in Table 10, we find that when a firm has no environmental committee, the effect of CEO abnormal climate exposure on carbon reduction becomes stronger, and when a firm has an environmental committee, the effect qualitatively remains but becomes statistically insignificant.

The results in Table 10 are consistent with the second explanation for our results in Table 8 and Table 9. It is unlikely, however, that the presence of environmental committee will inhibit a CEO's initiatives to reduce carbon emission. By contrast, it is more likely that CEO abnormal climate exposure is a beneficial substitute for other factors that can reduce firm carbon emission.

4.4.3 CEO power

Above we provide some indirect and suggestive evidence showing that CEO abnormal climate exposure is a substitute for other factors that promote carbon reduction. In this section, we will explore the effect of CEO power. If the effect on carbon reduction stems from a CEO's own willingness, then we should observe a stronger effect when a CEO is more powerful. Moreover, exploring the effect of CEO power can also help to rule out some other unobserved factors and provide more confidence on our conjecture. For example, if both CEO abnormal climate exposure and corporate carbon reduction are driven by an omitted variable, so that climate change promotes carbon reduction through other channels rather than CEOs, we should observe similar effects in powerful CEOs and less powerful CEOs. By contrast, if climate change promotes carbon reduction through CEOs, more powerful CEOs should be able to have stronger reactions.

We classify our sample into two sub-groups based on CEO power measured in different ways. The first classification criterion is CEO duality. Dual CEOs who are also chairpersons are considered to be more powerful as they also dominant in the board (Finkelstein and D'aveni, 1994; Brickley, Coles and Jarrell, 1997; Goergen, Limbach and Scholz-Daneshgari, 2020); the second criterion is whether a CEO is around her retiring age of 64-66 defined by Jenter and Lewellen (2015). Retiring CEOs are considered to be less powerful and are lee willing to utilize her influence in corporate decisions; for the third criterion, we follow Kale, Reis and Venkateswaran (2009) and Song and Wan (2019) and measure a CEO's relative compensation scale compared with other managers. If a CEO earns much more than other executives in the firm, the CEO is considered to be more powerful. Specifically, we calculate the total compensation of each manager and calculate the difference between CEO total compensation and the median of other non-CEO executives. We then divide the gap using the median of other non-CEO executives to construct the CEO relative compensation scale. A CEO is considered to be powerful if her relative compensation scale is above the sample median and less powerful otherwise. We lose a few observations due to the missing information on executives' compensation.

For each of the three measures of CEO power, we split our sample into two sub-samples for high CEO power and low CEO power and then replicate our baseline regression. Tables 11-13 present the results. Our results show that the effect of CEO climate change is only statistically significant and strong when the CEO is more powerful. More powerful CEOs are better at implementing carbon reduction, which provides us more confidence that the carbon reduction is CEO-driven.

4.4.4 Interpretation of the results and tests that rule out other possibilities

The results of information environment, environmental committee, and CEO power can be interpreted by three possible explanations. First, the effect following CEO abnormal climate exposure might actually motivate a corporate agency problem. On the one hand, CEOs may cut carbon emission for better reputation and their own interests. On the other hand, CEOs do this not for their own interest but simply for their sense of responsibility to the community while this may not be optimal for shareholders. Second, climate change reminds CEOs that firms can benefit from lower carbon emission so they conduct green washing which maximize shareholder economic benefits. Third, CEO abnormal climate exposure is actually a substitute for other factors that can promote environmental performance at no cost of profitability. When other factors are absent, CEO exposure can compensate the lack of those beneficial factors.

We provide three pieces of evidence that reject the first and second explanations. First, if the carbon reduction is beneficial for firms and shareholders, regardless whether it is greenwashing, this phenomenon should not only exist when more powerful CEOs try to implement these reductions. Second, we investigate the relationship between CEO abnormal climate change exposure firm financial performance. We measure firm performance using return on assets (ROA) which is defined as earnings before interest, tax, depreciation and amortization (EBITDA) over total assets. We also measure firm performance by annual stock return using data from CRSP. Table 14 present the results. We find no impact of CEO exposure on firm financial performance and this result holds for both the accounting and market measure. Our results still hold if we lag the climate exposure variable by one, two or three years. The negligible effect on firm performance indicates that CEO exposure neither improves or inhibits firm performance. The implication is that, on the one hand, the carbon reduction is unlikely to be at the cost of shareholder interests; and, on the other hand, the carbon emission is not driven by shareholder maximization.

Third, we obtain data of firms' ownership by funds from FactSet database. We use a textual analysis approach to identify green or ESG funds by interpreting their profiles. If a fund has ever mentioned some keywords and expressions such as "green", "ESG", "environment", "climate change", "carbon emission", "sustainability", "sustainable", "CO2", "greenhouse", "clean energy", etc in its profile, we classify this fund as a green fund. We then measure the shares and value of shares held by green funds in each firm's ownership. We replicate the baseline regressions by replacing the outcome variable with green fund ownership. The results are in Table 15. We find no increase in green fund investment after a CEO is exposed to more abnormal climate. This finding, together with our findings in corporate performance, indicate that firms cutting carbon emission following CEO abnormal climate exposure are unlikely to get engaged in green washing for more investment or better reputation, and are unlikely to erode shareholder interests.

5. Conclusion

In this paper, we study how CEO exposure to abnormal climate can affect corporate carbon emission. We find that a stronger contrast between recent climate exposure and past climate exposure will motivate a CEO to reduce corporate carbon emission. The results hold for both scaled carbon measure (emission intensity) and raw carbon measure (absolute emission). By measuring long-term abnormal climate in a CEO's hometown and comparing recent climate with that of a CEO's early-life formative years, we rule out as many potential confounded factors and other channels as possible. We find CEO hometown climate exposure has a stronger and more significant effect on corporate carbon emission reduction, and abnormal climate exposure in firm headquarter does not have such an effect.

We argue that CEOs keep caring their hometowns via various sources and the more they sense the abnormal climate against their formative years' memories, the more they cut their corporate carbon emission. We test this hypothesized channel by exploiting county-level data from Yale Climate Opinion

Map. We reveal that more exposure to abnormal climate can boost people's awareness towards climate change and raise their concerns on carbon emission.

Our abnormal climate exposure measure is novel and clean. We construct the measure based on both recent climate and a benchmark in early-life formative years. We thus avoid self-selection problems such as CEOs' families choose to migrate there because of certain family characteristics (Bernile, Bhagwat and Rau, 2017). By focusing on CEO hometown, we also avoid confounded factors such as regulators, other blockholders and firm substantive loss from exposure to abnormal climate. Furthermore, our measure, by construction, is exogenous, because we measure the ongoing abnormal climate in CEO's hometown, which is hard to predict. Moreover, we also provide evidence showing that the effect we reveal is not greenwashing and but a substitute for other beneficial factors that can promote a firm's environmental performance, and such carbon reduction is not at the cost of shareholder interests.

Taken together, our study reveals the importance of people's perception in green development, and also highlights the effects of dynamic time-variant CEO characteristics.

References

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

Adhikari, Binay K, 2016, Causal effect of analyst following on corporate social responsibility, *Journal of Corporate Finance* 41, 201-216.

Akerlof, Karen, Edward W Maibach, Dennis Fitzgerald, Andrew Y Cedeno, and Amanda Neuman, 2013, Do people "personally experience" global warming, and if so how, and does it matter?, *Global Environmental Change* 23, 81-91.

Alok, Shashwat, Nitin Kumar, and Russ Wermers, 2020, Do fund managers misestimate climatic disaster risk, *Review of Financial Studies* 33, 1146-1183.

Aswani, Jitendra, Aneesh Raghunandan, and Shivaram Rajgopal, 2024, Are carbon emissions associated with stock returns?, *Review of Finance*, 28, 75-106.

Azar, José, Miguel Duro, Igor Kadach, and Gaizka Ormazabal, 2021, The big three and corporate carbon emissions around the world, *Journal of Financial Economics* 142, 674-696.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis, 2020, Does climate change affect real estate prices? Only if you believe in it, *Review of Financial Studies* 33, 1256-1295.

Barron, Orie E, Donal Byard, and Oliver Kim, 2002, Changes in analysts' information around earnings announcements, *The Accounting Review* 77, 821-846.

Bénabou, Roland, and Jean Tirole, 2010, Individual and corporate social responsibility, *Economica* 77, 1-19.

Benmelech, Efraim, and Carola Frydman, 2015, Military CEOs, *Journal of Financial Economics* 117, 43-59.

Bernile, Gennaro, Vineet Bhagwat, and P Raghavendra Rau, 2017, What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior, *Journal of Finance* 72, 167-206.

Bernstein, Asaf, Stephen B Billings, Matthew T Gustafson, and Ryan Lewis, 2022, Partisan residential sorting on climate change risk, *Journal of Financial Economics* 146, 989-1015.

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

Boone, Audra L, and Joshua T White, 2015, The effect of institutional ownership on firm transparency and information production, *Journal of Financial Economics* 117, 508-533.

Brickley, James A, Jeffrey L Coles, and Gregg Jarrell, 1997, Leadership structure: Separating the CEO and chairman of the board, *Journal of corporate Finance* 3, 189-220.

Brody, Samuel D, Sammy Zahran, Arnold Vedlitz, and Himanshu Grover, 2008, Examining the relationship between physical vulnerability and public perceptions of global climate change in the united states, *Environment and Behavior* 40, 72-95.

Capstick, Stuart Bryce, and Nicholas Frank Pidgeon, 2014, Public perception of cold weather events as evidence for and against climate change, *Climatic Change* 122, 695-708.

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

Cornaggia, Jess N, Kimberly J Cornaggia, and Ryan D Israelsen, 2020, Where the heart is: Information production and the home bias, *Management Science* 66, 5532-5557.

Correa, Ricardo, Ai He, Christoph Herpfer, and Ugur Lel, 2020, The rising tide lifts some interest rates: Climate change, natural disasters and loan pricing, *Natural Disasters and Loan Pricing (October 13, 2020)*.

Cotter, Julie, Irem Tuna, and Peter D Wysocki, 2006, Expectations management and beatable targets: How do analysts react to explicit earnings guidance?, *Contemporary accounting research* 23, 593-624.

Custódio, Cláudia, and Daniel Metzger, 2014, Financial expert CEOs: CEO′ s work experience and firm′ s financial policies, *Journal of Financial Economics* 114, 125-154.

Deng, Xin, Jun-koo Kang, and Buen Sin Low, 2013, Corporate social responsibility and stakeholder value maximization: Evidence from mergers, *Journal of financial Economics* 110, 87-109.

Dhaliwal, Dan S, Oliver Zhen Li, Albert Tsang, and Yong George Yang, 2011, Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting, *Accounting Review* 86, 59-100.

Dittmar, Amy, and Ran Duchin, 2016, Looking in the rearview mirror: The effect of managers' professional experience on corporate financial policy, *Review of Financial Studies* 29, 565-602.

Fee, C Edward, Charles J Hadlock, and Joshua R Pierce, 2013, Managers with and without style: Evidence using exogenous variation, *Review of Financial Studies* 26, 567-601.

Feng, Xunan, and Anders C Johansson, 2018, Living through the great chinese famine: Early-life experiences and managerial decisions, *Journal of Corporate Finance* 48, 638-657.

Finkelstein, Sydney, and Richard A D'aveni, 1994, CEO duality as a double-edged sword: How boards of directors balance entrenchment avoidance and unity of command, *Academy of Management Journal* 37, 1079-1108.

Fischer, Claude S, Robert Jackson, C Ann Stueve, Kathleen Gerson, and Lynne M Jones, 1977, Networks and places: Social relations in the urban setting, in *Networks and Places* (Free Press, New York).

Garel, Alexandre, and Arthur Petit-Romec, 2022, CEO exposure to abnormally hot temperature and corporate carbon emissions, *Economics Letters* 210, 110156.

Giglio, Stefano, Matteo Maggiori, Krishna Rao, Johannes Stroebel, and Andreas Weber, 2021, Climate change and long-run discount rates: Evidence from real estate, *Review of Financial Studies* 34, 3527-3571.

Goergen, Marc, Peter Limbach, and Meik Scholz-Daneshgari, 2020, Firms' rationales for CEO duality: Evidence from a mandatory disclosure regulation, *Journal of Corporate Finance* 65, 101770.

Haque, Faizul, 2017, The effects of board characteristics and sustainable compensation policy on carbon performance of uk firms, *The British Accounting Review* 49, 347-364.

Hernández, Bernardo, M Carmen Hidalgo, M Esther Salazar-Laplace, and Stephany Hess, 2007, Place attachment and place identity in natives and non-natives, *Journal of Environmental Psychology* 27, 310-319.

Hidalgo, M Carmen, and Bernardo Hernandez, 2001, Place attachment: Conceptual and empirical questions, *Journal of Environmental Psychology* 21, 273-281.

Hodler, Roland, and Paul A Raschky, 2014, Regional favoritism, *The Quarterly Journal of Economics* 129, 995-1033.

Homroy, Swarnodeep, 2022, Ghg emissions and firm performance: The role of CEO gender socialization, *Journal of Banking & Finance* 106721.

Hong, Harrison, G Andrew Karolyi, and José A Scheinkman, 2020, Climate finance, *Review of Financial Studies* 33, 1011-1023.

Howe, Peter D, Ezra M Markowitz, Tien Ming Lee, Chia-Ying Ko, and Anthony Leiserowitz, 2013, Global perceptions of local temperature change, *Nature Climate Change* 3, 352-356.

Huang, Qiping, Yongjia Li, Meimei Lin, and Garrett A McBrayer, 2022, Natural disasters, risk salience, and corporate esg disclosure, *Journal of Corporate Finance* 72, 102152.

Huynh, Thanh D, and Ying Xia, 2021, Climate change news risk and corporate bond returns, *Journal of Financial and Quantitative Analysis* 56, 1985-2009.

Ilhan, Emirhan, Philipp Krueger, Zacharias Sautner, and Laura T Starks, 2021, Climate risk disclosure and institutional investors, *Swiss Finance Institute Research Paper*.

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

Iovino, Luigi, Thorsten Martin, and Julien Sauvagnat, 2021, Corporate taxation and carbon emissions, *Available at SSRN 3880057*.

Islam, Emdad, and Jason Zein, 2020, Inventor CEOs, *Journal of Financial Economics* 135, 505-527.

Jenter, Dirk, and Katharina Lewellen, 2015, CEO preferences and acquisitions, *Journal of Finance* 70, 2813-2852.

Jiang, Feng, Yiming Qian, and Scott E Yonker, 2019, Hometown biased acquisitions, *Journal of Financial and Quantitative Analysis* 54, 2017-2051.

Joireman, Jeff, Heather Barnes Truelove, and Blythe Duell, 2010, Effect of outdoor temperature, heat primes and anchoring on belief in global warming, *Journal of Environmental Psychology* 30, 358-367.

Kahn, Matthew E, and Matthew J Kotchen, 2011, Business cycle effects on concern about climate change: The chilling effect of recession, *Climate Change Economics* 2, 257-273.

Kale, Jayant R, Ebru Reis, and Anand Venkateswaran, 2009, Rank-order tournaments and incentive alignment: The effect on firm performance, *Journal of Finance* 64, 1479-1512.

Krosnick, Jon A, Allyson L Holbrook, Laura Lowe, and Penny S Visser, 2006, The origins and consequences of democratic citizens' policy agendas: A study of popular concern about global warming, *Climatic Change* 77, 7-43.

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

Krüger, Philipp, 2015, Corporate goodness and shareholder wealth, *Journal of Financial Economics* 115, 304-329.

Kunreuther, Howard, and Erwann Michel-Kerjan, 2007, Climate change, insurability of large-scale disasters and the emerging liability challenge, (National Bureau of Economic Research Cambridge, Mass., USA).

Leiserowitz, Anthony, 2006, Climate change risk perception and policy preferences: The role of affect, imagery, and values, *Climatic Change* 77, 45-72.

Liao, Lin, Le Luo, and Qingliang Tang, 2015, Gender diversity, board independence, environmental committee and greenhouse gas disclosure, *The British Accounting Review* 47, 409-424.

Lim, Ivan, and Duc Duy Nguyen, 2021, Hometown lending, *Journal of Financial and Quantitative Analysis* 56, 2894-2933.

Low, Setha M, and Irwin Altman, 1992, Place attachment, in *Place Attachment* (Springer).

Masulis, Ronald W, and Syed Walid Reza, 2015, Agency problems of corporate philanthropy, *Review of Financial Studies* 28, 592-636.

Mesch, Gustavo S, and Orit Manor, 1998, Social ties, environmental perception, and local attachment, *Environment and Behavior* 30, 504-519.

Nelson, Katherine, 1993, The psychological and social origins of autobiographical memory, *Psychological Science* 4, 7-14.

Nguyen, DD, S Ongena, S Qi, and V Sila, 2022, Climate change risk and the cost of mortgage credit, *Review of Finance*.

Nguyen, Duc Duy, Jens Hagendorff, and Arman Eshraghi, 2018, Does a CEO's cultural heritage affect performance under competitive pressure?, *Review of Financial Studies* 31, 97-141.

O'Connor, Robert E, Richard J Bard, and Ann Fisher, 1999, Risk perceptions, general environmental beliefs, and willingness to address climate change, *Risk Analysis* 19, 461-471.

O'Sullivan, Don, Leon Zolotoy, and Qingliang Fan, 2021, CEO early-life disaster experience and corporate social performance, *Strategic Management Journal* 42, 2137-2161.

Pankratz, Nora, and Christoph Schiller, 2021, Climate change and adaptation in global supply-chain networks, Proceedings of Paris December 2019 Finance Meeting EUROFIDAI-ESSEC, European Corporate Governance Institute–Finance Working Paper.

Pool, Veronika K, Noah Stoffman, and Scott E Yonker, 2012, No place like home: Familiarity in mutual fund manager portfolio choice, *Review of Financial Studies* 25, 2563-2599.

Qian, Cuili, Louise Y Lu, and Yangxin Yu, 2019, Financial analyst coverage and corporate social performance: Evidence from natural experiments, *Strategic Management Journal* 40, 2271-2286.

Semenza, Jan C, David E Hall, Daniel J Wilson, Brian D Bontempo, David J Sailor, and Linda A George, 2008, Public perception of climate change: Voluntary mitigation and barriers to behavior change, *American Journal of Preventive Medicine* 35, 479-487.

Shapiro, Joseph S, 2021, The environmental bias of trade policy, *The Quarterly Journal of Economics* 136, 831-886.

Sloggy, Matthew R, Jordan F Suter, Mani Rouhi Rad, Dale T Manning, and Chris Goemans, 2021, Changing climate, changing minds? The effects of natural disasters on public perceptions of climate change, *Climatic Change* 168, 1-26.

Smith, Adam B, and Richard W Katz, 2013, Us billion-dollar weather and climate disasters: Data sources, trends, accuracy and biases, *Natural Hazards* 67, 387-410.

Song, Wei-Ling, and Kam-Ming Wan, 2019, Does CEO compensation reflect managerial ability or managerial power? Evidence from the compensation of powerful CEOs, *Journal of Corporate Finance* 56, 1-14.

Spence, Alexa, Wouter Poortinga, Catherine Butler, and Nicholas Frank Pidgeon, 2011, Perceptions of climate change and willingness to save energy related to flood experience, *Nature Climate Change* 1, 46-49.

Stott, Peter A, Dáithí A Stone, and Myles R Allen, 2004, Human contribution to the european heatwave of 2003, *Nature* 432, 610-614.

Tschumi, Elisabeth, and Jakob Zscheischler, 2020, Countrywide climate features during recorded climate-related disasters, *Climatic Change* 158, 593-609.

Van Aalst, Maarten K, 2006, The impacts of climate change on the risk of natural disasters, *Disasters* 30, 5-18.

Williams, A Park, John T Abatzoglou, Alexander Gershunov, Janin Guzman-Morales, Daniel A Bishop, Jennifer K Balch, and Dennis P Lettenmaier, 2019, Observed impacts of anthropogenic climate change on wildfire in california, *Earth's Future* 7, 892-910.

Yonker, Scott E, 2017, Do managers give hometown labor an edge?, *Review of Financial Studies* 30, 3581-3604.

Tables

Table 1 Summary Statistics

This table displays the summary statistics of variables. Panel A include all the climate and disaster variables. Panel B displays firm variables including CEO characteristics. and Panel C displays county-level variables used in the channel test. All firm continuous variables are winsorized at the top and bottom 1% level. Definitions for variables are found in Table A1.

Panel A Climate measures	Mean	P25	Median	P75	Std	# Obs
Abnormal extreme days	0.227	-0.600	0.025	0.908	1.357	2,260
Abnormal hot days	0.745	-0.017	0.675	1.383	1.183	2,260
Abnormal cold days	-0.518	-1.025	-0.408	0.000	0.840	2,260
Abnormal maximum temperature	1.984	0.952	2.088	3.139	1.559	2,260
Abnormal minimum temperature	2.225	1.293	2.335	3.285	1.406	2,260
Abnormal mean temperature	2.465	1.530	2.582	3.536	1.408	2,260
Early disasters	0.099	0.000	0.000	0.100	0.182	2,260
Abnormal disasters	-0.019	-0.100	0.000	0.000	0.355	2,260
Abnormal extreme days HQ	0.206	-0.433	0.042	0.733	1.087	2,260
Abnormal hot days HQ	-0.083	-0.350	0.000	0.042	0.666	2,260
Abnormal cold days HQ	0.123	-0.592	0.000	0.725	1.178	2,260
Panel B Firm and CEO variables						
CO2 emission (Millions of tons)	8.151	0.171	1.010	5.085	21.931	2,260
Emission intensity (Kg per dollar)	0.468	0.016	0.044	0.250	1.255	2,260
Firm size	24.076	23.099	24.088	25.005	1.397	2,260
Book to market	0.407	0.191	0.343	0.539	0.331	2,260
ROA	0.128	0.078	0.122	0.173	0.074	2,260
Stock return	0.144	-0.038	0.123	0.299	0.349	2,260
PPE	0.287	0.082	0.192	0.477	0.252	2,260
Leverage	0.668	0.547	0.667	0.799	0.188	2,260
Environment score	62.567	48.684	65.679	78.594	20.209	1,905
ESG rating	7.164	6.000	7.000	8.000	1.817	1,904
Green fund ownership	0.058	0.029	0.044	0.068	0.058	2,260
Log of CEO age	4.057	3.989	4.060	4.127	0.108	2,260
Gender	0.938	1.000	1.000	1.000	0.240	2,260
Panel C County-level variables						
Unemployment Rate	5.126	3.600	4.700	6.200	2.108	18,340
Bachelor's degree	21.686	15.099	19.390	25.823	9.519	18,340
Log of GDP	13.934	12.811	13.763	14.825	1.593	18,340
Discuss (%)	30.852	27.787	30.047	33.041	4.483	15,284
Affect weather (%)	55.098	50.576	54.562	59.129	6.875	12,228
Regulate (%)	70.293	67.000	70.169	73.412	4.522	18,340

Table 2 Baseline results: CEO climate change experience and carbon emission

The table presents the baseline results. The outcome variable is Emission intensity, which is equal to CO2 emission scaled by revenue. The key variables for columns (1)-(2), (3)-(4) and (5)-(6) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. Columns (1), (3) and (5) control for industry, year and birth state fixed effects; columns (2), (4) and (6) control for firm, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission intensity	(2) Emission intensity	(3) Emission intensity	(4) Emission intensity	(5) Emission intensity	(6) Emission intensity
Abnormal extreme days	-0.071**	-0.040**				
	(0.031)	(0.016)				
Abnormal hot days			-0.065**	-0.032**		
			(0.033)	(0.014)		
Abnormal cold days					-0.060*	-0.039**
					(0.033)	(0.018)
Firm size	-0.063**	-0.205**	-0.061**	-0.203**	-0.057**	-0.200**
	(0.028)	(0.081)	(0.027)	(0.081)	(0.027)	(0.080)
Book to market	0.378***	0.184*	0.378***	0.187*	0.367***	0.185*
	(0.134)	(0.100)	(0.135)	(0.101)	(0.134)	(0.101)
ROA	-0.020	-0.950***	-0.040	-0.955***	-0.027	-0.933***
	(0.317)	(0.302)	(0.314)	(0.305)	(0.319)	(0.305)
PPE	0.370	-0.142	0.366	-0.137	0.396	-0.142
	(0.320)	(0.599)	(0.322)	(0.601)	(0.320)	(0.605)
Leverage	0.304*	0.198	0.300*	0.205	0.285*	0.199
	(0.162)	(0.185)	(0.161)	(0.188)	(0.158)	(0.187)
Log of CEO age	0.232	0.758	0.215	0.738	0.223	0.825
	(0.298)	(0.542)	(0.295)	(0.545)	(0.297)	(0.552)
Gender	0.087	0.093	0.090	0.094	0.093	0.096
	(0.115)	(0.351)	(0.115)	(0.354)	(0.116)	(0.358)
_cons	0.547	2.242	0.602	2.300	0.417	1.824
	(1.321)	(3.011)	(1.312)	(3.042)	(1.338)	(3.039)
N	2260	2232	2260	2232	2260	2232
R^2	0.717	0.932	0.716	0.932	0.715	0.932
Firm FE	No	Yes	No	Yes	No	Yes
Industry FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3 Alternative Measures of Climate Change Experiences

The table presents the baseline results with alternative measure of climate change experiences. The outcome variable is Emission intensity, which is equal to CO2 emission scaled by revenue. The key variables for columns (1), (2) and are abnormal maximum temperature, abnormal minimum temperature and abnormal mean temperature, respectively. All the columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission intensity	(2) Emission intensity	(3) Emission intensity
Abnormal max temperature	-0.053**		
	(0.026)		
Abnormal mean temperature		-0.068**	
		(0.029)	
Abnormal min temperature			-0.064**
			(0.028)
Firm size	-0.054**	-0.052**	-0.052*
	(0.027)	(0.027)	(0.026)
Book to market	0.372***	0.369***	0.366***
	(0.135)	(0.134)	(0.133)
ROA	-0.013	-0.021	-0.040
	(0.320)	(0.319)	(0.318)
PPE	0.376	0.370	0.370
	(0.323)	(0.322)	(0.320)
Leverage	0.294*	0.295*	0.292*
	(0.158)	(0.158)	(0.157)
Log of CEO age	0.158	0.178	0.212
	(0.289)	(0.291)	(0.294)
Gender	0.094	0.090	0.088
	(0.118)	(0.118)	(0.117)
_cons	0.730	0.662	0.517
	(1.310)	(1.314)	(1.322)
N	2260	2260	2260
R^2	0.716	0.716	0.716
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes

Table 4 Absolute Measure of Carbon Emission

The table presents the baseline results with absolute measure of climate change experiences. The outcome variable is CO2 emission in millions of tons. The key variables for columns (1), (2) and (3) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. All the columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) CO2 emission	(2) CO2 emission	(3) CO2 emission
Abnormal extreme days	-1.654***		
	(0.583)		
Abnormal hot days		-1.518***	
		(0.585)	
Abnormal cold days			-1.362**
			(0.631)
Firm size	3.768***	3.813***	3.887***
	(1.356)	(1.372)	(1.387)
Book to market	-2.050	-2.039	-2.293
	(3.588)	(3.612)	(3.658)
ROA	-9.802	-10.258	-9.986
	(10.451)	(10.590)	(10.536)
PPE	-29.163*	-29.256*	-28.565*
	(15.916)	(16.017)	(15.928)
Leverage	-5.573	-5.656	-6.019
	(5.407)	(5.444)	(5.500)
Log of CEO age	3.946	3.562	3.737
	(4.860)	(4.870)	(4.897)
Gender	-2.191	-2.131	-2.048
	(3.032)	(3.017)	(3.024)
_cons	-81.965**	-80.664**	-84.953**
	(32.683)	(32.738)	(33.782)
N	2260	2260	2260
R^2	0.624	0.622	0.619
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes

Table 5 Results Including Firm Headquarter Climate Change.

The table presents the results that rule out the effect of firm headquarter climate change in the past decade. The outcome variable is Emission intensity. The key variables for columns (1), (2) and (3) are abnormal extreme days, abnormal hot days and abnormal cold days in both CEO hometowns and firm headquarters, respectively. In columns (4), (5) and (6), we conduct a placebo test by removing CEO hometown climate change variables and only keeping firm headquarter climate change variables. All the columns control for industry and year fixed effects. Columns (1)-(3) further controls for CEO birth state fixed effects and columns (4)-(6) controls for firm headquarter state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission intensity	(2) Emission intensity	(3) Emission intensity	(4) Emission intensity	(5) Emission intensity	(6) Emission intensity
Abnormal extreme days	-0.074**					
	(0.034)					
Abnormal hot days		-0.070*				
		(0.036)				
Abnormal cold days			-0.059*			
			(0.033)			
Abnormal extreme days HQ	0.017			0.006		
	(0.024)			(0.022)		
Abnormal hot days HQ		0.025			0.016	
		(0.027)			(0.025)	
Abnormal cold days HQ			-0.007			-0.032
			(0.022)			(0.032)
Firm size	-0.063**	-0.061**	-0.057**	-0.064**	-0.064**	-0.064**
	(0.028)	(0.027)	(0.027)	(0.031)	(0.030)	(0.031)
Book to market	0.378***	0.376***	0.367***	0.401**	0.400**	0.400**
	(0.135)	(0.135)	(0.135)	(0.155)	(0.155)	(0.156)
ROA	-0.012	-0.033	-0.029	-0.534	-0.531	-0.541
	(0.318)	(0.315)	(0.319)	(0.392)	(0.390)	(0.390)
PPE	0.368	0.369	0.397	0.761*	0.763*	0.765*
	(0.320)	(0.323)	(0.320)	(0.389)	(0.391)	(0.389)
Leverage	0.306*	0.303*	0.285*	0.198	0.199	0.200
	(0.163)	(0.163)	(0.158)	(0.133)	(0.134)	(0.133)
Log of CEO age	0.230	0.211	0.222	0.107	0.105	0.106
	(0.297)	(0.294)	(0.298)	(0.349)	(0.349)	(0.351)
Gender	0.084	0.086	0.094	0.143	0.142	0.145
	(0.114)	(0.114)	(0.117)	(0.122)	(0.122)	(0.123)
_cons	0.563	0.620	0.415	1.032	1.035	1.026
	(1.313)	(1.305)	(1.337)	(1.505)	(1.506)	(1.508)
N	2260	2260	2260	2266	2266	2266
R^2	0.717	0.716	0.715	0.701	0.701	0.701
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	No	No	No
Headquarter FE	No	No	No	Yes	Yes	Yes

Table 6 Ruling out the Early-Life Disaster Effect

The table presents the results that further control for CEO fatal disaster experiences. The outcome variable is Emission intensity. In columns (1), (3) and (5), we further control for CEO early-life fatal disaster experiences. In columns (2), (4) and (6), we further control for CEO abnormal fatal disaster experiences. All the columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission intensity	(2) Emission intensity	(3) Emission intensity	(4) Emission intensity	(5) Emission intensity	(6) Emission intensity
Abnormal extreme days	-0.071**	-0.068**				
	(0.031)	(0.031)				
Abnormal hot days			-0.064*	-0.061*		
			(0.033)	(0.032)		
Abnormal cold days					-0.060*	-0.059*
					(0.033)	(0.033)
Early disasters	-0.127		-0.133		-0.140	
	(0.313)		(0.312)		(0.313)	
Abnormal disasters		0.203*		0.207*		0.216*
		(0.117)		(0.117)		(0.117)
Firm size	-0.063**	-0.064**	-0.061**	-0.062**	-0.058**	-0.059**
	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)	(0.027)
Book to market	0.377***	0.378***	0.377***	0.378***	0.366***	0.368***
	(0.133)	(0.136)	(0.133)	(0.136)	(0.133)	(0.136)
ROA	-0.050	-0.050	-0.071	-0.069	-0.061	-0.058
	(0.307)	(0.327)	(0.304)	(0.324)	(0.308)	(0.328)
PPE	0.352	0.400	0.348	0.397	0.376	0.426
	(0.335)	(0.323)	(0.337)	(0.324)	(0.336)	(0.323)
Leverage	0.308*	0.308*	0.304*	0.304*	0.289*	0.290*
	(0.163)	(0.162)	(0.163)	(0.161)	(0.160)	(0.158)
Log of CEO age	0.200	0.282	0.182	0.267	0.188	0.277
	(0.318)	(0.307)	(0.315)	(0.304)	(0.316)	(0.307)
Gender	0.085	0.101	0.088	0.104	0.091	0.108
	(0.114)	(0.120)	(0.115)	(0.120)	(0.115)	(0.121)
_cons	0.712	0.352	0.774	0.400	0.600	0.215
	(1.441)	(1.349)	(1.432)	(1.340)	(1.453)	(1.369)
N	2260	2260	2260	2260	2260	2260
R^2	0.717	0.718	0.716	0.718	0.715	0.717
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7 County-level climate change and local people's opinions.

The table presents the results that test our channel. The outcome variables for columns (1) and (4), (2) and (5), (3) and (6) are "discuss", "affect" and "regulate", respectively. In columns (1)-(3) the key variable is abnormal extreme days and its benchmark period is the decade that ends 20 years ago. In columns (4)-(6) the key variable is abnormal hot days and its benchmark period is the decade that ends 20 years ago. All the columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) discuss	(2) affect	(3) regulate	(4) discuss	(5) affect	(6) regulate
Abnormal extreme days 20	0.004***	0.013***	0.004***			
	(0.001)	(0.001)	(0.001)			
Abnormal hot days 20				0.006***	0.012***	0.002**
				(0.001)	(0.001)	(0.001)
Unemployment rate	0.143***	0.083***	0.024	0.144***	0.094***	0.025
	(0.014)	(0.017)	(0.020)	(0.014)	(0.017)	(0.020)
Bachelor's degree	0.108***		0.046***	0.108***		0.046***
	(0.009)		(0.013)	(0.009)		(0.013)
Log of GDP	0.089	0.585*	0.030	0.070	0.613**	0.038
	(0.175)	(0.304)	(0.218)	(0.175)	(0.303)	(0.218)
_cons	26.460***	46.371***	68.707***	26.675***	45.902***	68.620***
	(2.438)	(4.261)	(3.054)	(2.438)	(4.241)	(3.056)
N	15284	12228	18340	15284	12228	18340
R^2	0.963	0.978	0.911	0.963	0.978	0.910
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8 Sub-sample regressions by analyst coverage

The table presents the results in sub-samples classified by analyst coverage. The outcome variable is Emission intensity, which is equal to CO2 emission scaled by revenue. The key variables for columns (1)-(2), (3)-(4) and (5)-(6) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. Columns (1), (3) and (5) are observations with analyst coverage higher than sample median; columns (2), (4) and (6) are observations with analyst coverage lower than sample median. All columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission Density	(2) Emission Density	(3) Emission Density	(4) Emission Density	(5) Emission Density	(6) Emission Density
	Analyst < median	Analyst⩾ median	Analyst < median	Analyst⩾ median	Analyst < median	Analyst⩾ median
Abnormal extreme days	-0.143***	-0.024				
	(0.048)	(0.025)				
Abnormal hot days			-0.119**	-0.034		
			(0.046)	(0.032)		
Abnormal cold days					-0.159**	0.010
					(0.075)	(0.019)
Firm size	-0.107	-0.024	-0.101	-0.024	-0.099	-0.022
	(0.069)	(0.022)	(0.068)	(0.022)	(0.070)	(0.022)
Book to market	0.625***	-0.030	0.634***	-0.033	0.602***	-0.032
	(0.208)	(0.089)	(0.211)	(0.088)	(0.209)	(0.090)
ROA	-0.085	-0.391*	-0.083	-0.403*	0.001	-0.411*
	(0.735)	(0.228)	(0.731)	(0.227)	(0.763)	(0.228)
PPE	0.122	0.521**	0.099	0.512**	0.142	0.531**
	(0.793)	(0.238)	(0.800)	(0.240)	(0.803)	(0.236)
Leverage	0.520*	0.074	0.515*	0.078	0.527*	0.059
	(0.299)	(0.152)	(0.297)	(0.154)	(0.299)	(0.145)
Ln of CEO age	0.783	-0.222	0.756	-0.226	0.788	-0.232
	(0.691)	(0.242)	(0.692)	(0.240)	(0.701)	(0.238)
Gender	0.020	-0.008	0.001	-0.007	0.020	-0.002
	(0.187)	(0.137)	(0.191)	(0.138)	(0.188)	(0.139)
_cons	-0.478	1.658*	-0.433	1.679*	-0.809	1.643
	(3.203)	(0.991)	(3.213)	(0.984)	(3.258)	(0.998)
N	960	1295	960	1295	960	1295
R^2	0.754	0.712	0.751	0.712	0.750	0.712
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 9 Sub-sample regressions by MSCI climate change index

The table presents the results in sub-samples classified by inclusion of MSCI index. The outcome variable is Emission intensity, which is equal to CO2 emission scaled by revenue. The key variables for columns (1)-(2), (3)-(4) and (5)-(6) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. Columns (1), (3) and (5) are observations not included in the MSCI climate change index; columns (2), (4) and (6) are observations included in the MSCI climate change index. All columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission Density	(2) Emission Density	(3) Emission Density	(4) Emission Density	(5) Emission Density	(6) Emission Density
	Non-MSCI	MSCI	Non-MSCI	MSCI	Non-MSCI	MSCI
Abnormal extreme days	-0.082**	-0.005				
	(0.034)	(0.010)				
Abnormal hot days			-0.078**	-0.001		
			(0.038)	(0.008)		
Abnormal cold days					-0.064*	-0.016
					(0.034)	(0.036)
Firm size	-0.074**	0.001	-0.072**	0.000	-0.068*	0.000
	(0.036)	(0.011)	(0.036)	(0.011)	(0.035)	(0.011)
Book to market	0.433***	0.019	0.434***	0.021	0.419***	0.024
	(0.148)	(0.084)	(0.148)	(0.087)	(0.148)	(0.086)
ROA	-0.079	-0.467**	-0.102	-0.466**	-0.111	-0.449**
	(0.384)	(0.223)	(0.381)	(0.221)	(0.384)	(0.211)
PPE	0.336	-0.248	0.324	-0.244	0.363	-0.245
	(0.378)	(0.165)	(0.381)	(0.162)	(0.379)	(0.165)
Leverage	0.369**	-0.074	0.370**	-0.077	0.355**	-0.075
	(0.181)	(0.081)	(0.182)	(0.082)	(0.178)	(0.080)
Ln of CEO age	0.263	0.022	0.248	0.015	0.281	0.018
	(0.377)	(0.114)	(0.375)	(0.108)	(0.381)	(0.115)
Gender	0.133	0.063	0.137	0.064	0.140	0.065
	(0.144)	(0.045)	(0.145)	(0.046)	(0.147)	(0.048)
_cons	0.673	0.134	0.717	0.172	0.419	0.145
	(1.709)	(0.574)	(1.700)	(0.554)	(1.731)	(0.580)
N	1874	377	1874	377	1874	377
R^2	0.726	0.755	0.725	0.755	0.724	0.755
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10 Sub-sample regressions by environmental committee

The table presents the results in sub-samples classified by the presence of firm environmental committee. The outcome variable is Emission intensity, which is equal to CO2 emission scaled by revenue. The key variables for columns (1)-(2), (3)-(4) and (5)-(6) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. Columns (1), (3) and (5) are observations not having an environmental committee; columns (2), (4) and (6) are observations having an environmental committee. All columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission Density	(2) Emission Density	(3) Emission Density	(4) Emission Density	(5) Emission Density	(6) Emission Density
	No committee	Committee	No committee	Committee	No committee	Committee
Abnormal extreme days	-0.085**	-0.045				
	(0.039)	(0.050)				
Abnormal hot days			-0.084**	-0.028		
			(0.041)	(0.040)		
Abnormal cold days					-0.060*	-0.079
					(0.034)	(0.093)
Firm size	-0.069**	-0.333**	-0.066**	-0.329**	-0.062**	-0.325**
	(0.031)	(0.134)	(0.031)	(0.133)	(0.031)	(0.135)
Book to market	0.388**	0.244	0.392**	0.243	0.378**	0.241
	(0.159)	(0.205)	(0.160)	(0.206)	(0.159)	(0.206)
ROA	-0.049	-0.810	-0.066	-0.863	-0.059	-0.729
	(0.329)	(1.166)	(0.325)	(1.163)	(0.329)	(1.221)
PPE	0.221	1.478	0.213	1.479	0.251	1.507
	(0.338)	(1.182)	(0.339)	(1.189)	(0.340)	(1.168)
Leverage	0.379**	-0.407	0.375**	-0.378	0.351**	-0.398
	(0.156)	(0.734)	(0.156)	(0.750)	(0.150)	(0.732)
Ln of CEO age	-0.063	3.155	-0.082	3.115	-0.067	3.065
	(0.311)	(2.184)	(0.307)	(2.178)	(0.311)	(2.200)
Gender	-0.004	0.146	0.000	0.142	-0.003	0.120
	(0.126)	(0.584)	(0.126)	(0.588)	(0.126)	(0.599)
_cons	1.951	-4.399	1.998	-4.327	1.768	-4.260
	(1.423)	(6.952)	(1.414)	(6.976)	(1.452)	(7.018)
N	1830	422	1830	422	1830	422
R^2	0.722	0.845	0.721	0.845	0.719	0.845
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 11 Sub-sample regressions by CEO duality

The table presents the results in sub-samples classified by the presence of firm environmental committee. The outcome variable is Emission intensity, which is equal to CO2 emission scaled by revenue. The key variables for columns (1)-(2), (3)-(4) and (5)-(6) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. Columns (1), (3) and (5) are observations whose CEO are also board chairs; columns (2), (4) and (6) are observations whose CEOs are not board chairs. All columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission Density	(2) Emission Density	(3) Emission Density	(4) Emission Density	(5) Emission Density	(6) Emission Density
	Duality	No duality	Duality	No duality	Duality	No duality
Abnormal extreme days	-0.086**	-0.033				
	(0.039)	(0.035)				
Abnormal hot days			-0.075*	-0.012		
			(0.041)	(0.029)		
Abnormal cold days					-0.079**	-0.084
					(0.038)	(0.063)
Firm size	-0.055*	-0.048	-0.053*	-0.042	-0.052*	-0.044
	(0.031)	(0.054)	(0.031)	(0.051)	(0.031)	(0.051)
Book to market	0.373**	0.325***	0.372**	0.320***	0.363**	0.311**
	(0.157)	(0.121)	(0.158)	(0.122)	(0.158)	(0.123)
ROA	0.068	-0.396	0.047	-0.427	0.051	-0.340
	(0.368)	(0.501)	(0.367)	(0.507)	(0.371)	(0.496)
PPE	0.305	0.482	0.300	0.466	0.344	0.467
	(0.548)	(0.522)	(0.552)	(0.521)	(0.549)	(0.518)
Leverage	0.476**	0.013	0.471**	0.000	0.469**	-0.008
	(0.224)	(0.145)	(0.224)	(0.147)	(0.221)	(0.146)
Ln of CEO age	0.514	-0.117	0.493	-0.135	0.506	-0.111
	(0.389)	(0.312)	(0.386)	(0.310)	(0.391)	(0.308)
Gender	-0.050	0.133	-0.048	0.139	-0.050	0.133
	(0.123)	(0.096)	(0.123)	(0.095)	(0.123)	(0.095)
_cons	-0.735	1.702	-0.649	1.643	-0.821	1.539
	(1.763)	(1.328)	(1.752)	(1.321)	(1.784)	(1.276)
N	1728	518	1728	518	1728	518
R^2	0.722	0.850	0.721	0.850	0.720	0.851
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 12 Sub-sample regressions by CEO retiring age

The table presents the results in sub-samples classified by the presence of firm environmental committee. The outcome variable is Emission intensity, which is equal to CO2 emission scaled by revenue. The key variables for columns (1)-(2), (3)-(4) and (5)-(6) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. Columns (1), (3) and (5) are observations whose CEOs are not around retiring age; columns (2), (4) and (6) are observations whose CEOs are at retiring age (64-66). All columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission Density	(2) Emission Density	(3) Emission Density	(4) Emission Density	(5) Emission Density	(6) Emission Density
	Not retiring	Retiring	Not retiring	Retiring	Not retiring	Retiring
Abnormal extreme days	-0.065**	-0.099				
	(0.029)	(0.138)				
Abnormal hot days			-0.060*	-0.083		
			(0.031)	(0.173)		
Abnormal cold days					-0.052	-0.121
					(0.033)	(0.111)
Firm size	-0.061**	0.047	-0.060**	0.035	-0.056**	0.049
	(0.027)	(0.090)	(0.027)	(0.089)	(0.027)	(0.092)
Book to market	0.354***	0.311	0.355***	0.339	0.345***	0.309
	(0.133)	(0.557)	(0.133)	(0.565)	(0.133)	(0.569)
ROA	-0.049	-0.995	-0.067	-0.925	-0.057	-1.088
	(0.306)	(2.139)	(0.303)	(2.239)	(0.307)	(2.270)
PPE	0.441	1.771	0.436	1.753	0.470	1.693
	(0.343)	(1.154)	(0.346)	(1.162)	(0.344)	(1.138)
Leverage	0.300*	0.471	0.298*	0.491	0.283*	0.413
	(0.165)	(0.964)	(0.165)	(1.000)	(0.162)	(0.986)
Ln of CEO age	0.268	-15.177*	0.256	-15.631*	0.252	-15.137*
	(0.277)	(8.156)	(0.275)	(8.410)	(0.274)	(8.475)
Gender	0.108	-0.544	0.110	-0.562	0.112	-0.572
	(0.106)	(0.619)	(0.106)	(0.642)	(0.106)	(0.694)
_cons	0.354	62.356*	0.396	64.577*	0.263	62.151*
	(1.211)	(33.559)	(1.205)	(34.810)	(1.223)	(35.059)
N	2062	184	2062	184	2062	184
R^2	0.735	0.861	0.735	0.860	0.734	0.860
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 13 Sub-sample regressions by CEO compensation disparity

The table presents the results in sub-samples classified by the presence of firm environmental committee. The outcome variable is Emission intensity, which is equal to CO2 emission scaled by revenue. The key variables for columns (1)-(2), (3)-(4) and (5)-(6) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. Columns (1), (3) and (5) are observations whose CEO compensation disparity is higher than the sample median; columns (2), (4) and (6) are observations whose CEO compensation disparity is lower than the sample median. All columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Emission Density	(2) Emission Density	(3) Emission Density	(4) Emission Density	(5) Emission Density	(6) Emission Density
	High disparity	Low disparity	High disparity	Low disparity	High disparity	Low disparity
Abnormal extreme days	-0.144***	-0.023				
	(0.047)	(0.027)				
Abnormal hot days			-0.112**	-0.035		
			(0.046)	(0.031)		
Abnormal cold days					-0.144**	0.018
					(0.058)	(0.045)
Firm size	-0.021	-0.096***	-0.023	-0.096***	-0.015	-0.091**
	(0.044)	(0.036)	(0.044)	(0.036)	(0.044)	(0.035)
Book to market	0.479**	0.448***	0.485**	0.449***	0.479**	0.437***
	(0.214)	(0.165)	(0.219)	(0.167)	(0.216)	(0.163)
ROA	0.468	0.241	0.399	0.240	0.462	0.220
	(0.533)	(0.476)	(0.527)	(0.475)	(0.547)	(0.469)
PPE	0.715	-0.156	0.726	-0.163	0.765	-0.141
	(0.730)	(0.370)	(0.742)	(0.372)	(0.734)	(0.363)
Leverage	0.229	0.492***	0.220	0.494***	0.238	0.473**
	(0.224)	(0.187)	(0.224)	(0.189)	(0.229)	(0.185)
Ln of CEO age	0.121	0.415	0.093	0.408	0.151	0.401
	(0.531)	(0.436)	(0.532)	(0.436)	(0.542)	(0.436)
Gender	0.308	0.025	0.303	0.025	0.287	0.029
	(0.246)	(0.103)	(0.250)	(0.102)	(0.252)	(0.103)
_cons	-0.334	0.622	-0.096	0.663	-0.678	0.558
	(1.997)	(2.006)	(1.985)	(2.004)	(2.068)	(2.009)
N	1080	1071	1080	1071	1080	1071
R^2	0.742	0.754	0.739	0.755	0.738	0.754
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 14 The impacts of CEO climate change experience on corporate financial performance

The table presents the results estimating the impacts of CEO climate change experience on corporate ESG performance. The outcome variable for columns (1), (3) and (5) is ROA, and the outcome variable for columns (2), (4) and (6) is annual stock return. The key variables for columns (1)-(2), (3)-(4) and (5)-(6) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. All columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) ROA	(2) Stock return	(3) ROA	(4) Stock return	(5) ROA	(6) Stock return
Abnormal extreme days	0.000	-0.007				
	(0.001)	(0.006)				
Abnormal hot days			-0.001	-0.000		
			(0.001)	(0.007)		
Abnormal cold days					0.003	-0.022*
					(0.002)	(0.011)
Firm size	-0.002	-0.002	-0.002	-0.001	-0.002	-0.002
	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)
PPE	0.073***	0.042	0.072***	0.044	0.072***	0.047
	(0.022)	(0.061)	(0.022)	(0.061)	(0.022)	(0.061)
Leverage	-0.068***	-0.035	-0.068***	-0.037	-0.068***	-0.036
	(0.022)	(0.055)	(0.022)	(0.055)	(0.023)	(0.055)
Ln of CEO age	0.043	-0.064	0.043	-0.066	0.042	-0.061
	(0.031)	(0.083)	(0.031)	(0.084)	(0.031)	(0.084)
Gender	0.014	0.043	0.014	0.043	0.014	0.043
	(0.011)	(0.029)	(0.011)	(0.029)	(0.011)	(0.029)
_cons	0.023	0.420	0.025	0.413	0.026	0.392
	(0.151)	(0.388)	(0.152)	(0.390)	(0.151)	(0.391)
N	2260	2260	2260	2260	2260	2260
R^2	0.432	0.272	0.432	0.271	0.432	0.273
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 15 The impacts of CEO climate change experience on green fund ownership

The table presents the results estimating the impacts of CEO climate change experience on green fund ownership. The outcome variable is the percentage of shareholdings by green funds. The key variables for columns (1)-(3) are abnormal extreme days, abnormal hot days and abnormal cold days, respectively. All columns control for industry, year and birth state fixed effects. Definitions for variables are found in Table A1. ***, **, and * denote significance at the 1%, 5%, and 10% level. In parentheses, standard errors are clustered on firm level. All firm continuous variables are winsorized at the top and bottom 1% level.

	(1) Green fund ownership	(2) Green fund ownership	(3) Green fund ownership
Abnormal extreme days	0.001		
	(0.001)		
Abnormal hot days		0.000	
		(0.001)	
Abnormal cold days			0.003
			(0.002)
Firm size	-0.001	-0.001	-0.001
	(0.002)	(0.002)	(0.002)
PPE	-0.007	-0.007	-0.007
	(0.018)	(0.018)	(0.018)
Leverage	-0.008	-0.008	-0.008
	(0.012)	(0.012)	(0.012)
Ln of CEO age	-0.038*	-0.037*	-0.038*
	(0.022)	(0.022)	(0.022)
Gender	0.003	0.003	0.003
	(0.011)	(0.011)	(0.011)
_cons	0.242**	0.243**	0.247**
	(0.101)	(0.101)	(0.101)
N	2260	2260	2260
R^2	0.300	0.299	0.300
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Birth state FE	Yes	Yes	Yes

Figures

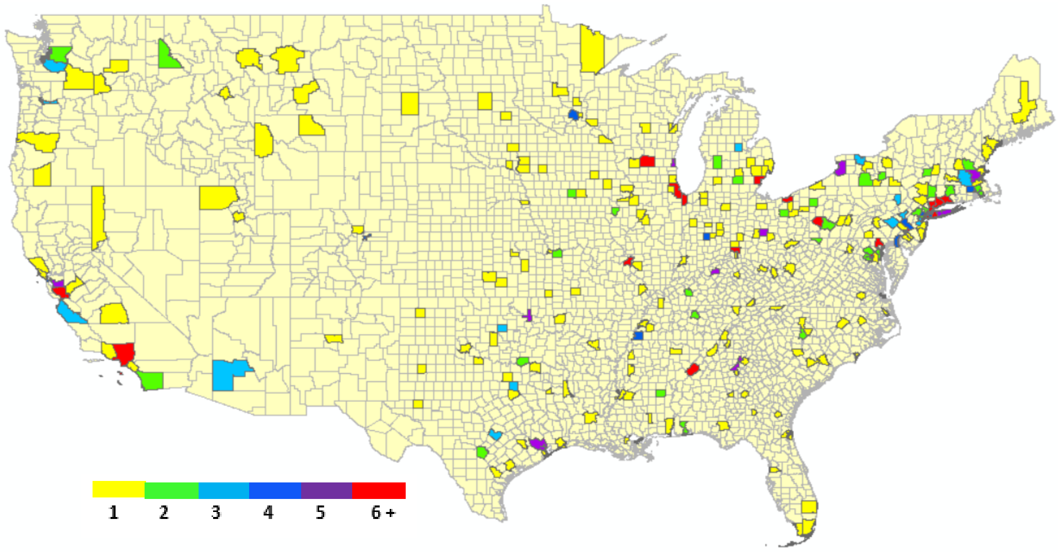

Figure 1 County-level Distribution of Sample CEO Birthplace

This figure displays the distribution of CEO birth counties in the sample. Most counties provide one CEO while some counties provide more. The numbers below the banner indicate how many CEOs in our sample come from each county.

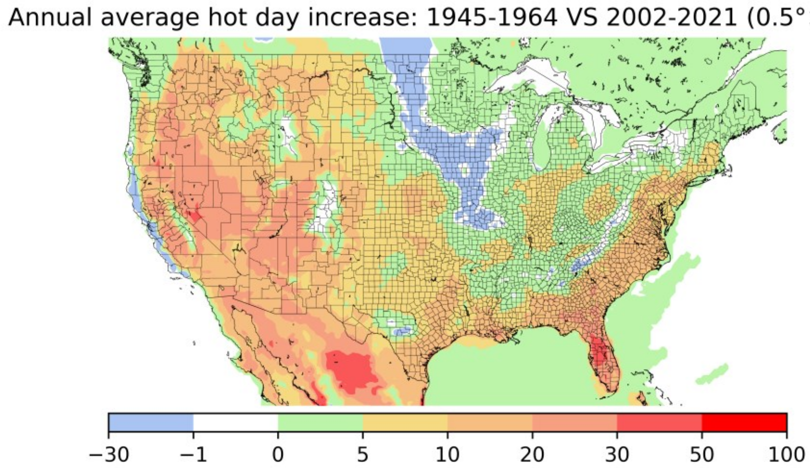

Figure 2 Annual Average Hot Day Increase: 1945-1964 and 2002-2021 (0.5°×0.5°)
This figure plots the difference of annual average hot days of two periods (1945-1964 and 2002-2021). For each grid, we count the total number of hot days in each year and calculate the annual average for each period, and then we obtain the difference by subtracting the value of 1945-1964 from the value of 2002-2021. The resolution of the grids is 0.5°×0.5°.

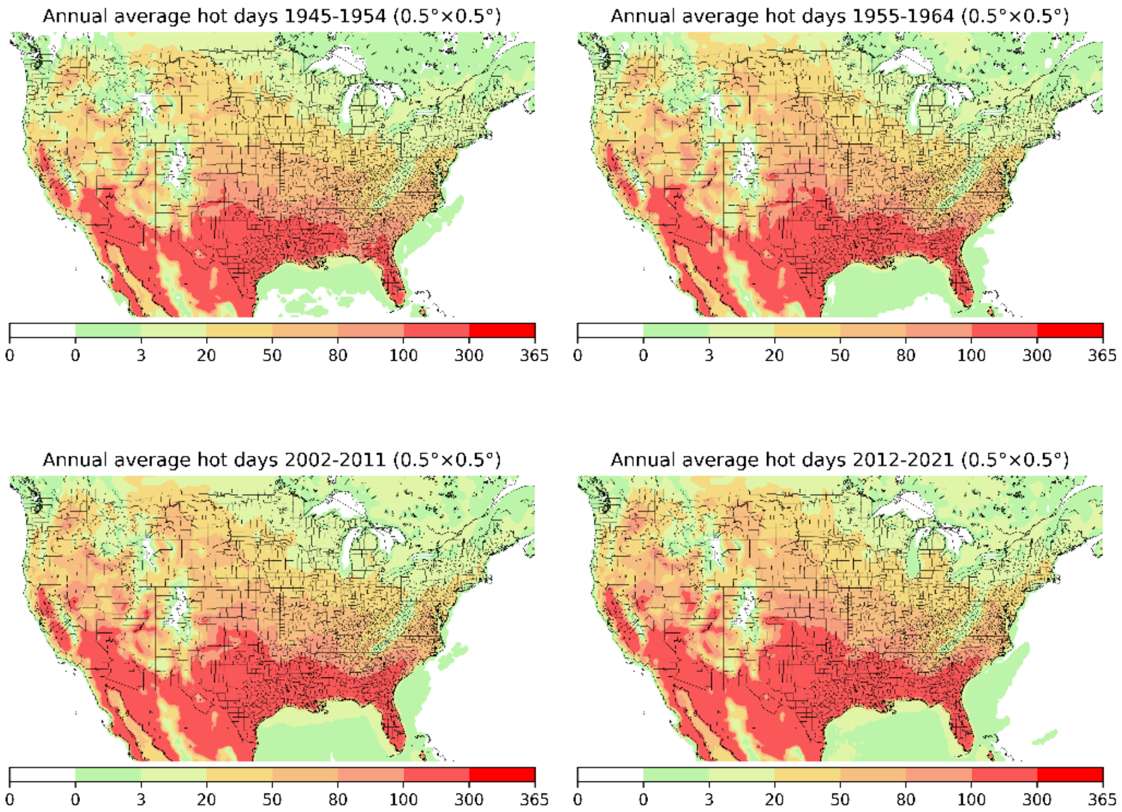

Figure 3 Annual Average Hot Day in Four Decades of 1945-1954, 1955-1964, 2002-2011 and 2012-2021 (0.5°×0.5°)

This figure plots average annual hot days of four different decades (1945-1954, 1955-1964, 2002-2011 and 2012-2021). For each grid, we count the total number of hot days in each year and calculate the annual average for each period. We plot the values of the four periods in four graphs. The resolution of the grids is 0.5°×0.5°.

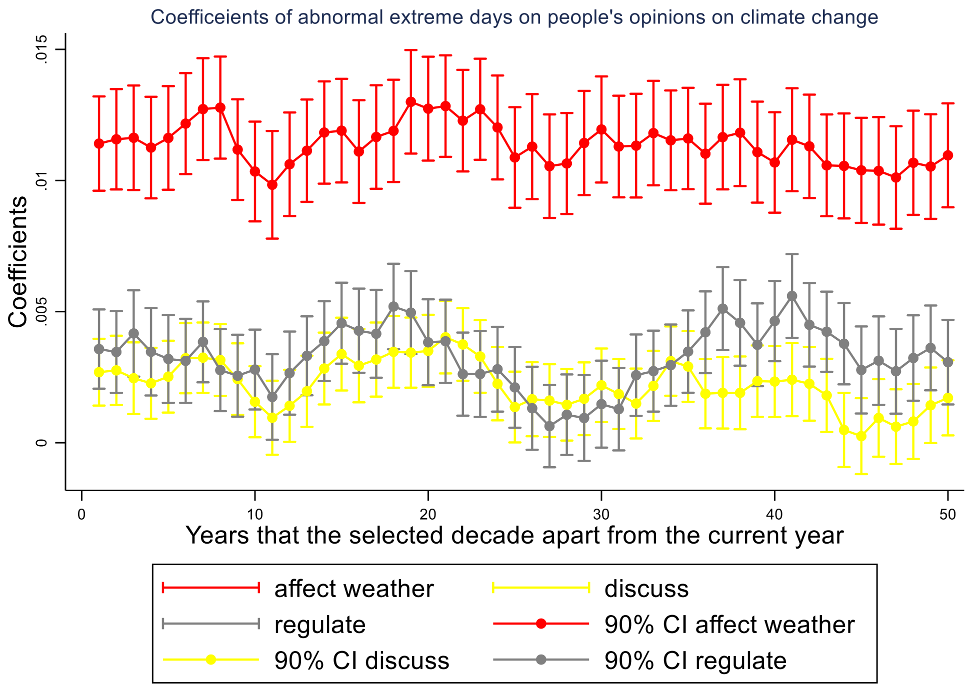

Figure 4 Coefficients of abnormal extreme days on people's opinions on climate change.

Figure 5 displays the coefficients and 90% confidence intervals of the same regression specification in Table 7. We use abnormal hot days measured by different time spans. The measure is the same to our main variables constructed as the difference between current year and a decade average. The values on horizontal axis denote how many years the end year of the benchmark decade is apart from the current year. The selected time span traverses every year from one to fifty.

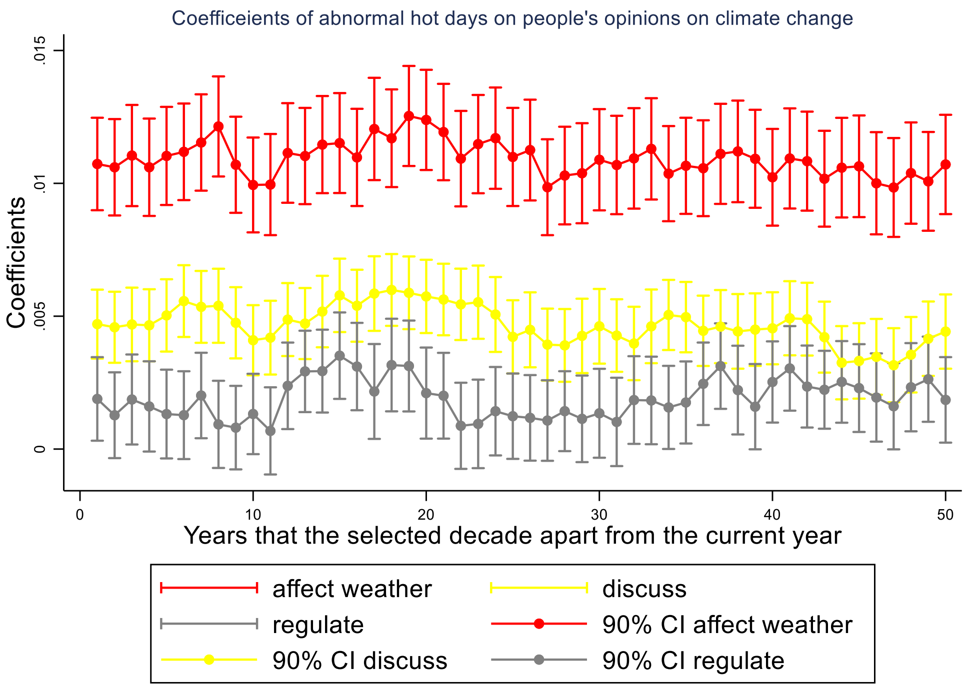

Figure 5 Coefficients of abnormal extreme hot days on people's opinions on climate change.
Figure 5 displays the coefficients and 90% confidence intervals of the same regression specification in Table 7. We use abnormal extreme days measured by different time spans. The measure is the same to our main variables constructed as the difference between current year and a decade average. The values on horizontal axis denote how many years the end year of the benchmark decade is apart from the current year. The selected time span traverses every year from one to fifty.

Appendix

Table A1 Variable Definition

Variables	Definitions
Panel A Climate measures	
Abnormal extreme days	The monthly abnormal number of extreme days of a certain year in a CEO's hometown. An extreme day is defined as a day temperature higher than 30℃ or lower than 0℃. The measure is constructed as the difference between a current year's value and the average of a benchmark period. The benchmark period for this measure is a CEO's formative decade during 5-15 years old
Abnormal hot days	The monthly abnormal number of hot days of a certain year in a CEO's hometown. A hot day is defined as a day temperature higher than 30℃. The measure is constructed as the difference between a current year's value and the average of a benchmark period. The benchmark period for this measure is a CEO's formative decade during 5-15 years old
Abnormal cold days	The monthly abnormal number of cold days of a certain year in a CEO's hometown. A hot day is defined as a day temperature lower than 0℃. The measure is constructed as the difference between a current year's value and the average of a benchmark period. The benchmark period for this measure is a CEO's formative decade during 5-15 years old
Abnormal maximum temperature	The monthly abnormal maximum temperature of a certain year in a CEO's hometown. The measure is constructed as the difference between a current year's value and the average of a benchmark period. The benchmark period for this measure is a CEO's formative decade during 5-15 years old
Abnormal minimum temperature	The monthly abnormal minimum temperature of a certain year in a CEO's hometown. The measure is constructed as the difference between a current year's value and the average of a benchmark period. The benchmark period for this measure is a CEO's formative decade during 5-15 years old
Abnormal mean temperature	The monthly abnormal mean temperature of a certain year in a CEO's hometown. The measure is constructed as the difference between a current year's value and the average of a benchmark period. The benchmark period for this measure is a CEO's formative decade during 5-15 years old
Early disasters	The average number of fatal disasters during a CEO's formative decade
Abnormal disasters	The abnormal number of fatal disasters in a current year. The measure is constructed as the difference between a current year's value and the average of a benchmark period. The benchmark period for this measure is a CEO's formative decade during 5-15 years old
Abnormal extreme days HQ	The monthly abnormal number of extreme days of a certain year in a firm's headquarter. The measure is constructed as the difference between a current year's value and the average of a benchmark period. The benchmark period for this measure is the past decade
Abnormal hot days HQ	The monthly abnormal number of hot days of a certain year in a firm's headquarter. The measure is constructed as the difference between a current year's value and the average of a

	benchmark period. The benchmark period for this measure is the past decade
Abnormal cold days HQ	The monthly abnormal number of cold days of a certain year in a firm's headquarter. The measure is constructed as the difference between a current year's value and the average of a benchmark period. The benchmark period for this measure is the past decade
Panel B Firm and CEO variables	
CO2 emission (Millions of tons)	Firm absolute volume of carbon emission
Emission intensity (Kg per dollar)	=CO2 emission / revenue
Firm size	Logarithm of total assets
Book to market	Book to market ratio
ROA	Return on assets=EBITDA/total assets
PPE	=Fixed assets / total assets
Leverage	=long-term debt / total assets
Log of CEO age	Logarithm of CEO age
Gender	CEO gender, =1 for male and 0 for female
Panel C County-level variables	
Unemployment Rate	Employment rate in each county
Bachelor's degree	The percentage of people having a Bachelor's degree in a county
Log of GDP	Logarithm of a county's GDP
Discuss (%)	The percentage of people often discussing climate change with people around
Affect weather (%)	The percentage of people believing that global warming is affecting US weather
Regulate (%)	The percentage of people supporting that CO2 emission should be regulated as a pollutant

Table A2 Sample construction

	#
All firm-year observations with non-missing values of carbon emission from Refinitiv database	**6,955**
Less:	
CEOs without birthplace information	(4,592)
Observations with missing values in control variables in **Table A1**.	(9)
Final sample:	**2,354**
Less: Singleton observations (as a result of interacted fixed effects)	(94)
Effective observations in Column 1, Table 2	**2,260**