The Response of Local Corporate Sustainability to Environmental Disasters: Evidence from Wildfires*

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Abstract

Environmental disasters are thought to increase the focus on corporate sustainability in the communities where they occur. Extracting data on wildfires and using ESG ratings and EPA air enforcement actions to construct measures of local corporate sustainability, we study this conjecture. To address the omitted variables concern, we conduct a pre- and post-trends analysis and an instrumental variables analysis using the recently developed Hot-Dry-Windy Index. We show that severe wildfires in a county increase significantly its corporate environmental sustainability in the following year. The impact is stronger in counties with a high fraction of climate change believers or Democratic voters.

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1. Introduction

Climate change has made natural disasters more common, endangering wildlife and generating substantial economic costs. Given this increasingly threatening situation, society has called on corporations to step up and make up for the damage caused by these events.[1] At the same time, many firms engage in projects of sustainability at the request of their stakeholders, who consider it desirable for profit maximization or behavioral reasons.

The literature has documented an increase in corporate giving in the wake of disasters. There is evidence that firms respond to a disaster faster and offer larger donations, if they are headquartered in the country (e.g., Muller and Whiteman (2009), Ballesteros, Useem, and Wry (2017)), and especially near the city (e.g., Crampton and Patten (2008), Tilcsik and Marquis (2013)), where it occurs. As reported by Johnson, Connolly, and Carter (2011), the activities of corporate giving have a wide range (e.g., giving cash grants to the impacted families, buying gear and equipment for the fire and rescue agencies, setting up educational or training programs for the community) and could be involved in multiple stages of a crisis (e.g., mitigation or preventive planning).[2]

Our paper uses wildfires to extend the impact of environmental disasters from corporate giving to corporate sustainability — and to the local corporate environmental sustainability in particular. That is, we examine whether the occurrence of a wildfire in a given area will prompt the local firms to take more environmentally conscious actions, such as decreasing pollution and waste, increasing the use of renewable sources of energy, or adjusting their environmental management systems to reduce the climate change risk. Wildfires are a frequent type of environmental disaster in the U.S., that is widely discussed by ecologists and environmental scientists, and has been shown to be associated with deforestation and global

[1] E.g., Danziger, P. N., "Fire, Floods, Hurricanes: How And Why Corporations Must Help", *Forbes*, October 20, 2017.

[2] Other notable responses to disasters from the local corporations include the increase in their cash holdings (Dessaint and Matray (2017)) and the acquisition of larger firms with high cash flows in different industries (Gormley and Matsa (2011)).

warming. Indicatively, according to the Monitoring Trends in Burn Severity (MTBS), every year about 1,000 large fires take place in the U.S. burning approximately 6 million acres.

We thus develop an empirical framework to examine two hypotheses about the effects of wildfires on corporate sustainability. Our first hypothesis is that wildfires affect positively the corporate environmental sustainability in the areas where they take place. However, at the same time, we also anticipate a heterogeneity in this response based on the local climate change beliefs as well as political partisanship (e.g., Baldauf, Garlappi, and Yannelis (2020), Hazlett and Mildenberger (2020)). In other words, our second hypothesis is that the local corporate environmental sustainability increases after a wildfire, only if the community has an eco-friendly inclination.

Our analysis is conducted at the county level. To construct the main dependent variable of our regressions, we collect the widely used corporate sustainability data from the MSCI ESG KLD STATS database. We then compute an environmental sustainability index for every company in the Russell 3000 Index, taking into account both strengths and concerns of a firm's sustainability profile. Next, we calculate the average value of this index in a given county, weighting by the size of each local firm. This local portfolio represents an aggregate rating for a county's corporate environmental sustainability. Consequently, the annual changes of this measure express the improvement in the local corporate environmental sustainability.

Overall, our data set is an unbalanced panel of 587 different counties spanning from the year 2003 to 2016. Around 24% of these counties experience a wildfire during the sample period. Our explanatory variable is the severity of a wildfire in a county in a given year, which we measure using the percentage of its area that is burned. To calculate it, we extract data from the MTBS project.

We then regress the annual change of a county's corporate environmental sustainability on the fraction of its area that is burned by wildfires in the year before. To account for predetermined differences, we include county fixed effects, year fixed effects, and controls for counties' contemporaneous characteristics. To make sure that our results are not driven by areas with small firms, we weigh our regressions by the total size of a county's firms.

Testing our first hypothesis, we find indeed that, if a county experiences severe wildfires in a given year, then the environmental sustainability of its companies increases significantly in the following year. Specifically, considering also the counties without any wildfire event, a one standard deviation increase in the fraction of a county's burned area approximately doubles the annual change of its corporate environmental sustainability relative to the average.

The result continues to hold if we include additional control variables that might be related to a county's wildfire severity and corporate environmental sustainability. For instance, we consider the controlled burns that are set intentionally to protect or restore the forests. We also factor in the wildfires that take place in neighboring counties or, more generally, the attention that a county's population pays to non-local wildfires as these are taking place. In regressions where we respectively include the percentage of a county's area burned by prescribed fires, the highest wildfire burned fraction of a neighboring county, or the Google searches for fires in the designated market area to which a county is assigned, the coefficient estimate of the county's own wildfire severity is virtually unchanged.

We also do a placebo test, where we investigate if wildfires impact aspects of corporate sustainability that are non-environmental. In the MSCI ESG KLD STATS database, there are six other components: diversity, community, employees, human rights, products, and corporate governance. If there is a strong effect from wildfires on these other types of corporate sustainability, then our result for the corporate environmental sustainability is likely to be driven by omitted variables. However, in regressions where the dependent variable is the annual change in each of these aspects, the estimated coefficient of the wildfire severity is always statistically insignificant.

One worry in our setup is the potential presence of pre-trends. For instance, firms might be able to anticipate an environmental disaster in their area, and therefore start improving their environmental sustainability in advance of its occurrence. In this case, the effect that we estimate does not originate from the wildfires, but is part of the implementation of an agenda that is planned in advance. To examine this possibility, we repeat the estimation using as a dependent variable the one- or two-year lagged annual change of a county's corporate environmental sustainability. The coefficient of the fraction of a county's wildfire burned area is found to be small, negative and statistically insignificant, implying that the aforementioned scenario is unlikely to be true.

Similarly, we test for the existence of post-trends. That is, we examine whether the local corporate environmental sustainability decreases or continues to rise in the years following a wildfire. To this end, we rerun our regressions using as a dependent variable the one- or two-year forward annual change of a county's corporate environmental sustainability. The estimated coefficient of the wildfire severity is small and statistically not different from zero. This means that a severe wildfire induces an increase in the local corporate environmental sustainability right after its occurrence, which is not temporary, but it does not contribute to any further growth in the later years.

We further show that our result is robust in subsamples where we remove the observations with very high wildfire severity, the counties in the state of California, the counties with a low fraction of forest area, or the counties which do not show up in every year of our period. We additionally experiment with alternative measures of wildfire severity based solely on the occurrence of wildfires or the acres burned by them. Importantly, we examine whether our result is contingent on the sustainability data from the MSCI ESG KLD STATS database. As an alternative, we consider a smaller sustainability data set on firms in the Russell 1000 Index during the years 2010-2017, which are extracted from Morningstar's Sustainalytics. None of our conclusions is substantially altered.

Even so, an omitted variable bias in our empirical setup may still be possible. To buttress the causal interpretation of our findings, we conduct an instrumental variable analysis using the Hot-Dry-Windy Index of Srock, Charney, Potter, and Goodrick (2018). This is a recently developed wildfire predictor that relies exclusively on the local atmospheric conditions, which we can measure at NOAA's weather stations. The IV estimate that we obtain for the coefficient of wildfire severity is also sizeable and actually larger than the OLS estimate. Our exclusion restriction states that the Hot-Dry-Windy Index affects the local corporate environmental sustainability only through the wildfires that it might cause. Its plausibility is supported by subsample tests that show an insignificant impact of the index on counties' corporate environmental sustainability change given the absence or presence of a wildfire.

To test our second hypothesis, i.e., the heterogeneous response of communities based on their eco-friendly inclination, we redo the analysis in county subsamples. We first examine the heterogeneity of the impact of wildfire severity between counties with high and low population fraction of climate change believers, as defined by a variety of measures in the Yale Climate Opinion Maps (Howe, Mildenberger, Marlon, and Leiserowitz (2015)). We find that the effect on corporate environmental sustainability is significant only in counties with a high fraction of climate change believers.

In the same spirit, we examine if the effect diverges between Democratic and Republican counties, using the ratio of votes in the presidential elections from the MIT Election Lab. Analogously, we find that it is significant only in the Democratic counties. At the same time, balance tests indicate that all these groups of counties could experience similar wildfires during the sample period, thus lowering the chances that our results reflect a selection bias. Our second hypothesis is therefore supported by the data.

In sum, the wildfire-induced increase in the local corporate environmental sustainability that we identify provides at least some consolation in the aftermath of wildfires. It resembles the natural disasters-induced adoption of risk-mitigating technologies documented by Miao and Popp (2014).[3] More broadly, another takeaway from our results is that wildfires can contribute to the faster implementation of the environmental commitments that local firms

[3] In other work, parallel to ours, Huang, Li, McBrayer, and Lin (2020) estimate increases in the disclosure transparency of the local corporate sustainability after natural disasters recorded in the Spatial Hazard Events and Losses Database for the United States, while Chu, Liu, and Tian (2021) estimate increases in the local corporate green innovation after spills reported in the U.S. Coast Guard's National Response Center.

have made (e.g., Bolton and Kacperczyk (2021)), as well as to the better compliance with the environmental mandates of institutional investors (e.g., Hong, Wang, and Yang (2021)).

Of course, in practice, the process to decarbonize and switch to renewables is long-term and gradual (e.g., consider the net-zero emissions target by 2050 of the Paris Agreement). It is thus useful to look at whether the increase in local corporate environmental sustainability which we measure based on ratings is compatible with local corporate environmental sustainability outcomes in the interim. One such type of outcomes, often viewed as essential for the honesty and effectiveness of any corporate environmental sustainability effort, involves the local changes in the number of air enforcement actions from the EPA. At a bare minimum, these should decrease, if the local corporate environmental sustainability increases.

Indeed, in the last part of our paper, we estimate significant decreasing effects of the wildfire severity on the local changes of the formal air enforcement. A one standard deviation increase in the fraction of a county's wildfire burned area decreases its annual change in the number of air formal enforcement actions by around 3 times relative to the average, and its annual change in the number of air penalties by around 10 times relative to the average. Notably, we find no impact on the local change of the air stack tests number, suggesting that the above changes are less likely to be driven by an increase in the regulators' leniency.

We also again document similar conclusions from the heterogeneity analysis based on the counties' climate change beliefs and political partisanship. In light of the ongoing carbon tax debate between Democrats and Republicans, it would be interesting in future research to focus on counties where the increase in local corporate environmental sustainability is found to be insignificant, and investigate whether a more active and targeted promotion of green financial products after an environmental disaster would change this result to any extent.

2. Hypotheses

In their review, Bénabou and Tirole (2010) discuss three reasons for which firms might engage in sustainability. First, sustainability could protect and extend their time horizon against legislative actions and activists (e.g., it could relax regulatory scrutiny and lower fines). A second reason is delegated philanthropy: consumers, investors and employees may be willing to forego some direct utility from their firms, if they know that the latter are doing some good. The first two reasons are consistent with profit maximizing. In contrast, the third reason is behavioral and asserts that corporate insiders care about philanthropy, and thus divert resources from their fiduciary duties towards altruistic projects for their own motives (e.g., to gain attention or power in their community).

The framework implied by these theories in normal times is depicted in Subfigure 1a. Moreover, a fourth distinct reason for which firms take sustainability actions is mitigation. The premise is that, if done collectively, sustainability could potentially lower the probability of disaster arrivals.

For any of these reasons, since environmental disasters raise the awareness of the environmental risk in the areas where they take place, they are expected to act as a wake-up call for the enhancement of the local corporate environmental policies. Especially given the destruction that wildfires cause to forests and wildlife, and their association with global warming, our first hypothesis (depicted in Subfigure 1b) states that:

> **H1:** Wildfires increase the corporate environmental sustainability in the counties where they occur.

At the same time, it is clear that not all stakeholders promote sustainability. For example, Dyck, Lins, Roth, and Wagner (2019) find that only when investors come from countries with a strong communal belief in environmental or social issues do they push for the firm to exert sustainability efforts in these areas. Analogously, within the U.S., we should expect that firms in counties with a large fraction of believers in climate change would be more likely to respond to a environmental disaster. Similarly, given the divergence between the two major American political parties on this issue, and the fact that differences in political ideologies are usually translated to different investment choices (e.g., Hong and Kostovetsky (2012)), we expect that partisan differences may generate different reactions to these events. We therefore propose a second hypothesis (depicted in Subfigure 1c):

> **H2:** The effect of wildfires on the corporate environmental sustainability in a county depends on its communal beliefs about climate change and its political partisanship.

3. Data

3.1. Counties' corporate environmental sustainability

To measure counties' corporate sustainability, we extract data at the firm-year-level from the MSCI ESG KLD STATS database. The main advantage of this widely used data set over data sets from alternative providers is that it covers all the publicly traded firms in the Russell 3000 universe. Our sample period spans from 2003 to 2016. For every year, we observe the 3,000 largest (in terms of market capitalization) publicly listed companies, which together represent approximately 98% of the entire U.S. stock market.[4] We are therefore able to obtain a good picture of the corporate sustainability situation in the country. Our main focus is on the environmental performance indicators, though later we also use the data on firms' diversity, community, employees, human rights, products, and corporate governance to test if the exposure to wildfires has an impact on a county's non-environmental aspects of sustainability.

In the data, each aspect of a firm's environmental sustainability in a given year has several categories of strengths and concerns, each of which results in a score of 0 or 1. For example, in terms of strengths, a firm might use clean energy sources or technologies that limit waste

[4]For details, see the report on "Russell US Indexes - 40 years of insights", *FTE Russell*, June 28, 2019.

disposal and carbon emissions. On the other hand, in terms of concerns, a firm might produce more emissions than allowed by its permits, or face public criticism and perhaps even lawsuits over contributing to global warming or biodiversity reduction. We note that each indicator measures only the extensive margin with respect to a given attribute (e.g., if a firm faces a concern about its waste, it might decrease its level but still remain at the same index value, if the decrease is not enough). The full list of strengths and concerns is provided in online Appendix Table 1.

A straightforward measure of a firm's overall environmental sustainability in a given year used by the literature is the difference between the sum of its strengths and the sum of its concerns. Yet, since the maximum number of strengths and concerns varies by year, we use instead the recently refined metric of Lins, Servaes, and Tamayo (2017), which allows for consistent comparisons during the sample period. Specifically, the environmental sustainability of firm j in year t is rated by the following equation:

$$EnvSust_{j,t} = 100 \times \left(\frac{\#EnvStr_{j,t}}{\#EnvStr_t} - \frac{\#EnvConc_{j,t}}{\#EnvConc_t} \right). \tag{1}$$

$\#EnvStr_{j,t}$ is the number of firm j's environmental sustainability strengths in year t, $\#EnvConc_{j,t}$ is the number of firm j's environmental sustainability concerns in year t, $\#EnvStr_t$ is the maximum number of environmental sustainability strengths among all firms in year t, and $\#EnvConc_t$ is the maximum number of environmental sustainability concerns among all firms in year t. In other words, before taking their difference, both the strengths and concerns of a firm are scaled by the highest number they can respectively attain in a given year. The resulting measure thus ranges from -100 to 100 in every year.

Next, we aggregate firms' environmental sustainability at the county level. We assign firms to counties using the address ZIP-Code of their headquarters from the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) — as provided by McDonald's Augmented 10-X Header Data.[5] Overall, there are 587 different counties in the sample,

[5] https://sraf.nd.edu/data/augmented-10-x-header-data

which roughly corresponds to an 18% coverage of all the U.S. counties and reflects the clustering of corporate headquarters in few cities. Of course, to the extent that firms have multiple divisions and branches, their sustainability may be encountered in additional areas (e.g., Akey and Appel (2021), Bartram, Hou, and Kim (2021)). For the purposes of this study, however, we focus on the counties of firms' headquarters, since this is where their top management and other important stakeholders tend to live.

We can then calculate the value-weighted portfolio of a county's corporate environmental sustainability based on its local firms, as follows:

$$\overline{EnvSust}_{i,t} = \sum_{j \in \mathcal{N}_{i,t}} \frac{Size_{j,t}}{TotSize_{i,t}} EnvSust_{j,t} \tag{2}$$

where $\mathcal{N}_{i,t}$ is the set of firms in county i in year t, $Size_{j,t}$ is the size (i.e., book value, market capitalization, or total assets) of firm j in year t, and $TotSize_{i,t} \equiv \sum_{j \in \mathcal{N}_{i,t}} Size_{j,t}$ is the total size of all the firms headquartered in county i in year t. This index expresses the average corporate environmental sustainability in a given county based on the perspective that each local firm's contribution is proportional to its relative size.

In our analysis, we focus on the yearly changes of this index. However, we need to make sure that any changes that occur in the corporate environmental sustainability in a given county are the result of changes in the corporate environmental sustainability of its local firms, as opposed to changes in its local firms' sizes. We thus fix firms' sizes to their levels in the previous year and use the following difference:

$$\Delta\overline{EnvSust}_{i,t} = \sum_{j \in \mathcal{N}_{i,t}} \frac{Size_{j,t-1}}{TotSize_{i,t-1}} (EnvSust_{j,t} - EnvSust_{j,t-1}). \tag{3}$$

Below, we calculate the above expression using firms' book value as their size, while, in the online Appendix, we recalculate it using firms' market capitalization and total assets. Independent of the proxy for firm size, the measured changes in counties' corporate environmental sustainability are similar.

The summary statistics of these changes, which comprise the dependent variable in our framework below, are presented in Panel A of Table 1. The mean change is 0.528, which indicates that, on average, the corporate environmental sustainability in counties increases over time. The median change is zero, while the standard deviation is 7.161, indicating a substantial variation.

3.2. Wildfire severity

To determine how much counties in the United States are affected by wildfires, we draw data from the Monitoring Trends in Burns Severity (MTBS), which is provided by the U.S. Geological Survey and the U.S. Department of Agriculture.[6] As described by Eidenshink, Schwind, Brewer, Zhu, Quayle, and Howard (2007), MTBS uses satellite remote sensing data to map the extent of large fires (i.e., those burning over 500 acres). It details the mapping of each fire as a polygon, represented by the coordinates of its edges in the shapefile format.

At the same time, we obtain the county TIGER/Line shapefiles from Census. Based on the maps of wildfires and counties, we use Python and its Geopandas module to calculate their intersections, which are subsequently used to estimate the fraction of the area in county i that is burned in year t (denoted by $BurnedFrac_{i,t}$). This is the key explanatory factor in our analysis. The geographical distribution of the average fraction of the wildfire burned area in every U.S. county during the sample period 2003-2016 is depicted in Figure 2. Most counties in the West as well as in the state of Florida experience a wildfire during that time.

The figure additionally depicts with black dots the address ZIP-codes of the headquarters of the the Russell 3000 firms, for which the corporate sustainability data are available. As described above, our focus is on the 587 different counties that contain these firms. The wildfire severity for these regions is summarized in Panel A of Table 1. Considering also the counties without any wildfires, the annual fraction of a county's wildfire burned area is on average 0.087% and has a standard deviation of 0.691%. Its median is zero, reflecting that

[6] https://www.mtbs.gov/direct-download

in more than half of our county-year observations there is no wildfire event (i.e., about 24% of the counties with Russell 3000 firms experience a wildfire during the sample period).

3.3. Controls

We obtain financial information for the Russell 3000 companies from Compustat. We focus on their book value, market capitalization and total assets, each of which can be used as an alternative measure for their size in Eq. (3). We define the controls of a county to be the (log of the) total market capitalization of its companies ($LogMarketCap$) and the ratio of their total book value over its income ($RATIO$), which, as in Hong, Kubik, and Stein (2008), indicates the degree of dependence of the local economy on the local stocks.

For each county, we also extract the annual log population ($LogPop$) and income per capita ($LogIncPerCap$) from the Bureau of Economic Analysis (BEA), and the annual unemployment rate ($Unemp$) from the Bureau of Labor statistics (BLS). All the controls are summarized in Panel B of Table 1.

4. Estimation

4.1. Empirical framework

To examine the impact of wildfires on the change of a county's corporate environmental sustainability, we use the following empirical specification:

$$\Delta\overline{EnvSust}_{i,t} = \alpha + \beta BurnedFrac_{i,t-1} + \boldsymbol{\gamma}'\boldsymbol{X}_{i,t-1} + \delta_i + \theta_t + \epsilon_{i,t}. \quad (4)$$

$\Delta\overline{EnvSust}_{i,t}$ is county i's change of corporate environmental sustainability in year t, and $BurnedFrac_{i,t-1}$ is county i's fraction of wildfire burned area in year $t-1$. $\boldsymbol{X}_{i,t-1}$ represents the vector of control variables for county i in year $t-1$. County fixed effects are denoted by δ_i and control for all counties' time-invariant factors that might affect the change of their corporate environmental sustainability as well as the occurrence and severity of wildfires (e.g., their geography). On the other hand, year fixed effects are denoted by θ_t and control for the annual variation in the change of corporate environmental sustainability that is common across all the counties. As usual, $\epsilon_{i,t}$ is the random, mean independent, disturbance term.

4.2. Main result

The results from the estimation of Eq. (4) are presented in Table 2. To ensure that our estimates are not driven by counties with small firms, we weigh our regressions by the total size of county i's firms in year $t-1$, as measured by their book value.[7] In Column 1, where we include only county fixed effects and year fixed effects, the estimated coefficient of the past year's fraction of wildfire burned area ($BurnedFrac_{i,t-1}$) is 0.779 and has a t-statistic of 4.43. In Column 2, where we add all counties' controls, the estimated coefficient of the fraction of wildfire burned area is 0.800 with a t-statistic 4.26, and hence very similar to its previous value. None of the controls seems to matter, with the exception of a county's ratio of its firms' total book value over its income ($RATIO$).

For a visualization of the estimate, we draw, in Subfigure 3a, the scatter plot of counties' residualized corporate environmental sustainability change (i.e., their demeaned and detrended change) against the fraction of their wildfire burned area. Since most counties do not experience any wildfire during the sample period, most observations are concentrated at the zero value of the fraction of wildfire burned area. However, the positive slope of the fitted line in the graph indicates that if a county experiences a wildfire, then its corporate environmental sustainability tends to increase with the severity of the disaster.

The corresponding economic effect (taking into account counties without wildfires) is that a one standard deviation increase in the fraction of a county's wildfire burned area increases its corporate environmental sustainability change by 105% $\left(\approx \frac{0.800 \cdot 0.691}{0.528}\right)$ relative

[7] In online Appendix Table 2, we reestimate Eq. (4) using firms' market capitalization (in Panel A) and total assets (in Panel B) to calculate the change in counties' corporate environmental sustainability and weigh our regressions. The estimates that we obtain for the coefficient of wildfire severity are very similar. The respective scatter plots drawn in online Appendix Figure 1 are also similar to Subfigure 3a.

to the average. In other words, a one standard deviation increase in the wildfire severity approximately doubles the growth of a county's corporate environmental sustainability.

4.3. Inclusion of additional control variables

4.3.1. Prescribed fires

From the MTBS database, we also extract data on the prescribed fires. These are set intentionally in order to protect the health of forests, and might thus serve as a substitute for the corporate environmental sustainability in a county. We then introduce in Eq. (4) county i's fraction of area burned by prescribed fires in year $t-1$ (denoted by $PrescrFrac_{i,t-1}$) and repeat the estimation in Column 1 of Table 3. The estimated coefficient of the burned fraction by prescribed fires is found to be negative, but statistically significant only at the 10% confidence level. Importantly, the estimated coefficient of the burned fraction by wildfires is almost the same as before.

4.3.2. Wildfires in neighboring counties

Wildfires can often spread to multiple counties and, even if they do not, might create other predicaments such as a smoke fog for a number of days. We hence consider the highest fraction of area burned by wildfires in county i's neighboring counties in year $t-1$ (denoted by $BurnedFracNeighbor_{i,t-1}$). As shown in online Appendix Table 3, the correlation between this variable and the fraction of county i's own wildfire burned area is statistically significant. Column 2 of Table 3 reports the results when both aforementioned variables are included in Eq. (4). The estimated coefficient of the wildfire severity in neighboring counties is low and statistically insignificant (i.e., -0.139 with a t-statistic of -1.04), while the estimated coefficient of a county's own wildfire severity is very similar to its previous value.

4.3.3. Attention of locals to wildfires

A county's population might also pay attention to wildfires which are not local or nearby. For example, counties in New York might keep track of wildfires that take place in California. To capture the interest that county i shows in wildfires during year $t-1$, we calculate the average value of the Google search index for "fires" in its designated market area at the dates when a (local or non-local) wildfire occurs in that year (denoted by $SearchFire_{i,t-1}$).[8] This variable is also expected to express the extent of wildfires' media coverage in a county. As shown in online Appendix Table 3, a county's interest is higher for its own severe wildfires.

The estimation results when we include the above variable in Eq. (4) are presented in Column 3 of Table 3. Since the data on Google searches start in 2004, we focus on the subperiod 2004-2016. The estimated coefficient of local interest for wildfires is nearly zero and statistically insignificant. In contrast, the estimated coefficient of the wildfire severity has a similar value (i.e., around 0.9) and a t-statistic higher than 3. As in the case with the wildfires in neighboring counties, this suggests that wildfires increase a county's corporate environmental sustainability provided that they take place in its area.

4.4. Placebo test using the local non-environmental sustainability

We also run a placebo test where we examine if wildfires impact other non-environmental aspects of a county's corporate sustainability. If they do, then it is likely that the previous result for the corporate environmental sustainability change is driven by omitted factors. Using the MSCI ESG KLD STATS database, we reformulate Eq. (1), (2), and (3), in order to obtain the changes in local corporate sustainability that refer to the (i) diversity, (ii) community, (iii) employees, (iv) human rights, (v) products, and (vi) corporate governance. Their summary statistics are shown in Panel C of Table 1.

We then reestimate Eq. (4) with each of these six variables in the left-hand side. The results from the placebo regressions are presented in Table 4. Regardless of the particular

[8] The methodology to construct this variable is analogous to the one by Branikas and Buchbinder (2021).

non-environmental aspect of the local corporate sustainability change, the estimated coefficient of the wildfire severity is always statistically insignificant (with the absolute value of its t-statistic being at most equal to 1).

4.5. Pre- and post-trends analysis

4.5.1. Testing for pre-trends

A potential concern for us is that pre-trends may conflate the estimation of the wildfire severity effect. For example, suppose that some counties which have not yet experienced a wildfire have programs that predict the enhancement of their future corporate environmental sustainability. If wildfires take place in these counties afterwards, our estimate is not causal.

If this scenario were true, then we would also expect an increase in the corporate environmental sustainability of counties that experience a wildfire before its occurrence. But this implication can be tested by rerunning Eq. (4) using as a new dependent variable counties' past corporate environmental sustainability changes. The results from these regressions are presented in Panel A of Table 5. In Column 1, the dependent variable is county i's one-year lagged corporate environmental sustainability change ($\Delta\overline{EnvSust}_{i,t-1}$), while, in Column 2, the dependent variable is county i's two-year lagged corporate sustainability environmental change ($\Delta\overline{EnvSust}_{i,t-2}$). In both columns, the estimated coefficient of county i's fraction of wildfire burned area in year $t-1$ ($BurnedFrac_{i,t-1}$) is small, negative, and statistically insignificant, which suggests that the aforementioned scenario is unlikely to hold.

4.5.2. Testing for post-trends

We also look to see if the increase that a wildfire induces on the local corporate environmental sustainability is reversed or further enhanced in the years that follow. Specifically, we repeat the estimation of Eq. (4) using as a new dependent variable counties' forward environmental sustainability changes and present the results in Panel B of Table 5. In Column 1, where the dependent variable is county i's one-year forward corporate environmental sustainability change ($\Delta \overline{EnvSust}_{i,t+1}$), the estimated coefficient of county i's fraction of wildfire burned area in year $t-1$ ($BurnedFrac_{i,t-1}$) is slightly negative and statistically not different from zero. In Column 2, where the dependent variable is county i's two-year forward corporate environmental sustainability change ($\Delta \overline{EnvSust}_{i,t+2}$), the coefficient estimate of the wildfire severity is slightly positive and also not statistically significant.

For a visualization of the pre- and post-trends analysis' results, we summarize them both (together with our baseline result from the previous subsection) in Figure 4, depicting the point estimates (with a white dash) and the corresponding 95% confidence intervals (with solid black lines). Overall, wildfire severity does not affect the change in a county's corporate environmental sustainability in the years prior to a wildfire, but only right after it occurs. Moreover, there is no other impact in the later years.

4.6. Other robustness checks

4.6.1. Removing observations with very high wildfire severity or CA counties

Since there are many counties without any wildfire during the sample period, there might be a worry that observations with very high wildfire severity are influential in terms of driving our result. Yet, as can be seen in Subfigure 3a, a line with a positive slope can be fitted even if we omit the spheres on the far right. Indicatively, in Column 1 of online Appendix Table 4, where we repeat the estimation of Eq. (4) after dropping observations with a burned fraction higher than 10%, the estimated coefficient increases to 1.133 with a t-statistic 5.67.

Similarly, we investigate if our result is robust to omitting the counties in California. As shown in Figure 2, these counties are among the most severely burned areas in our period. Inevitably, since quite a few large firms in the Russell 3000 Index have their headquarters in the state of California, an important part of the U.S. corporate sustainability is omitted as well, when we remove these counties. Nevertheless, as illustrated in Column 2 of online Appendix Table 4, the estimated coefficient of wildfire severity in this subsample ends up being close to the baseline and statistically significant at the 5% confidence level (i.e., it is equal to 0.809 with a t-statistic of 2.13).

4.6.2. Removing counties with a low fraction of forest area

A necessary condition for a county to experience a wildfire is to have forests in the first place. That is, if a county has a low fraction of forest area, then only a low fraction of its total area can be burned. The presence of counties with a low fraction of forest area might overestimate the effect of wildfire severity, if their corporate environmental sustainability decreases over time. Of course, in such a case, we would expect to find a pre- and post-trend wildfire severity effect, which as we show in Subsection 4.5 is absent.

But to be conservative, we also consider explicitly the fraction of forest area in a county. To calculate it, we use the FIA Landcover County Estimates 2016 provided by the Forest Service of the United States Department of Agriculture. We then repeat the estimation of Eq. (4) in online Appendix Table 5, after dropping counties whose fraction of forest area is less than the 10% or 25% percentile. In both cases, the estimated coefficient of the wildfire severity is found to be similar.

4.6.3. Balanced panels of counties

We also repeat the estimation of Eq. (4) in balanced panels of counties in online Appendix Table 6. In Panel A, where we focus only on the counties that are observed in every year of the sample period, the estimated coefficient of the wildfire severity is very similar to the estimated coefficient in the whole sample (in terms of both magnitude and statistical significance). Moreover, in Panel B, we construct another balanced panel of counties, that is a subset of the former. Specifically, we consider only the Russell 3000 firms that show up in every year, and the counties where these are headquartered.[9] For these counties, we

[9] There might be a concern that wildfires affect companies' location decisions. However, in our data, wildfires do not predict the change in the number of local firms.

recalculate the changes of their corporate environmental sustainability based on Eq. (3). The resulting coefficient of wildfire severity is slightly higher.

4.6.4. Alternative measures of wildfire severity

We also experiment with alternative measures of wildfire severity. In Panel A of online Appendix Table 7, we simply use an indicator variable that is equal to one if county i experiences a wildfire in year $t-1$ (denoted by $FireDum_{i,t-1}$). Controlling for counties' characteristics, the estimated coefficient of the wildfire indicator is 3.667 with a t-statistic of 3.75. This implies that the occurrence of wildfires increases the local corporate environmental sustainability change by roughly $7\left(\approx \frac{3.667}{0.528}\right)$ times relative to the average.

Furthermore, in Panel B, we use the log of the acres of county i' burned area in year $t-1$ plus one (denoted by $LogBurnedAcres_{i,t-1}$), which expresses the wildfire severity in absolute terms (i.e., without taking into account the total area in a county). The estimated coefficient with full controls is 0.246 and has a t-statistic of 4.25. This means that an increase in the acres of a county's burned area by 10 percentage points increases the change in its corporate environmental sustainability by almost 5% $\left(\approx \frac{0.246\cdot 10\%}{0.528}\right)$ relative to the average.

4.6.5. Alternative corporate sustainability data from Sustainalytics

Recently, the literature on corporate sustainability has noted a discrepancy in the ratings of firms from different sustainability data providers (e.g., Berg, Koelbel, and Rigobon (2020)). Therefore, our estimate for the effect of wildfire severity on the local corporate environmental sustainability might be contingent on the sustainability data that we draw from the MSCI ESG KLD STATS database. To ameliorate this concern, we draw alternative sustainability data from Morningstar's Sustainalytics.

The data that we extract readily contain three firm-level scores about the environmental, social, and governance sustainability (called respectively E-score, S-score, and G-score) and cover all the firms in the Russell 1000 Index (which, in terms of market capitalization, represent around 92% of the U.S. stock market) during the period 2010-2017. Hence, there is an attrition in the number of firms and years of our sample. The correlation between a firm's environmental sustainability as defined by Eq. (1) in the MSCI ESG KLD STATS database and its environmental score in Sustainalytics is approximately 0.5, indicating that there is at least some consensus on how to rate the environmental aspect of corporate sustainability.

As before, we assign firms to counties using the address ZIP-Code of their headquarters. The derived sample is an unbalanced panel of 248 different counties (corresponding roughly to an 8% coverage of all the U.S. counties). Their corporate sustainability changes and wildfire severity are summarized in Panel A of online Appendix Table 8.

We then reestimate Eq. (4) in Panel B of the same table. Independently of whether we control for counties' characteristics, the estimated coefficient of wildfire severity is positive and statistically significant. With full controls, it is equal to 0.633 with a t-statistic of 4.52. Thus, in this sample, a one standard deviation increase in the fraction of a county's wildfire burned area increases its corporate environmental sustainability change by around 45% $\left(\approx \frac{0.633 \cdot 0.475}{0.672}\right)$ relative to the average. This economic effect is smaller than the one that we estimate using the MSCI ESG KLD STATS data for a larger set of counties, but it is still sizable.

As regards the effects of wildfire severity on the local corporate social or governance sustainability change, they are both found to be small and statistically insignificant. Hence, even using this alternative data set, we find no impact on the non-environmental aspects of sustainability. In Panel C, we check again for pre- or post-trends, and we obtain as before insignificant estimates.

4.7. Instrumental variable analysis

4.7.1. The Hot-Dry-Windy Index

Although we check for pre- and post-trends and go over a number of robustness exercises, there might still be a concern about an omitted variable bias in our empirical setup. To address it, we conduct an instrumental variable analysis using the Hot-Dry-Windy (HDW) Index of Srock, Charney, Potter, and Goodrick (2018) as an instrument. This is a recently developed wildfire predictor that depends exclusively on the local atmospheric conditions. Specifically, a county's HDW Index on a given day is defined to be the highest product of its wind speed and vapor pressure deficit recorded on that day. In notation, letting $WND_{i,h}$ and $VPD_{i,h}$ be respectively county i's wind speed and vapor pressure deficit recorded at time h, and $\mathcal{H}_{i,d}$ be the set of recording times on day d, county i's HDW Index on day d is:

$$HDW_{i,d} = \max_{h \in \mathcal{H}_{i,d}} \left\{ WND_{i,h} \cdot VPD_{i,h} \right\}. \tag{5}$$

To calculate counties' HDW Index, we extract from their weather stations in NOAA hourly data on the wind speed as well as the air and dew point temperatures (which are required for the calculation of the vapor pressure deficit).[10] Since the variables' frequency in Eq. (4) is annual, we first compute the daily values of the index, and then take the average value in each county for a given year. Before the averaging process, we drop counties with missing daily observations, which leads us to an unbalanced panel of 443 different counties.

To ensure that we only use counties' variation with respect to their annual HDW Index (as opposed to other aspects of their weather) in our analysis below, we also calculate and include as additional controls in our regressions counties' average annual high temperature, wind speed and vapor pressure deficit. The logarithms of all these weather variables are summarized in Panel D of Table 1.

4.7.2. The three-stage estimation method

Since the fraction of counties' wildfire burned area is censored at zero, a standard 2SLS procedure produces estimates that are largely upward biased (Rigobon and Stoker (2009)).[11]

[10] These are available at https://www.ncei.noaa.gov/data/global-hourly/access. WND is in m/s, while $VPD \equiv e(\text{Air Temperature}) - e(\text{Dew Point Temperature})$, where $e(x) \equiv 6.11 \cdot 10^{\frac{7.5x}{237.3+x}}$, is expressed in hPa.

[11] The 95% two-step weak-instrument-robust confidence set according to Andrews, Stock, and Sun (2019), in our case, is equal to $[1.583, 67.191]$.

To tackle this issue (and at the same time avoid the pitfalls of "forbidden regressions"), we follow the guidelines of Angrist and Pischke (2008) and apply a three-stage estimation method.[12]

The first stage is a Tobit regression, described below:

$$BurnedFrac_{i,t-1} = \max\left\{\kappa + \lambda \log\left(\overline{HDW}_{i,t-1}\right) + \boldsymbol{\mu'} \boldsymbol{W}_{i,t-1} + \boldsymbol{\nu'} \boldsymbol{X}_{i,t-1} + \xi_i + \pi_{t-1} + \omega_{i,t-1}, 0\right\}. \quad (6)$$

$BurnedFrac_{i,t-1}$ is county i's fraction of wildfire burned area in year $t-1$, while $\log(\overline{HDW}_{i,t-1})$ is the log of its corresponding average HDW Index. $\boldsymbol{W}_{i,t-1}$ is a vector consisting of the logs of county i's average high temperature $\left(\log(\overline{HighTMP}_{i,t-1})\right)$, wind speed $\left(\log(\overline{HighWND}_{i,t-1})\right)$, and vapor pressure deficit $\left(\log(\overline{HighVPD}_{i,t-1})\right)$ in year $t-1$. $\boldsymbol{X}_{i,t-1}$ is the previous vector of controls, ξ_i and π_{t-1} are respectively county and year fixed effects, and $\omega_{i,t-1}$ is the standard normal error term.

The estimation results of the first stage are presented in Column 2 of Table 6. The coefficient of a county's log HDW Index is estimated to be 32.130 with a t-statistic of 2.89 (or equivalently an F-statistic of 8.35), which makes it the most statistically significant wildfire predictor among all the weather variables.[13] The corresponding marginal effect, calculated at the means of the covariates, is 4.551. This means that an increase in a county's HDW Index by 10 percentage points is expected to increase its wildfire severity by around 5 $\left(\approx \frac{4.551 \cdot 10\%}{0.087}\right)$ times relative to the average.

We then proceed with a 2SLS estimation of Eq. (4) using the Tobit values of Eq. (6) as an instrument. That is, our second stage is a linear regression of $BurnedFrac_{i,t-1}$ on the nonlinear fitted values $\widehat{BurnedFrac}^{Tobit}_{i,t-1}$ which we obtain from the first stage. And subsequently, the third stage is a linear regression of $\Delta\overline{EnvSust}_{i,t}$ on the linear fitted values

[12] A similar econometric method is applied by Adams, Almeida, and Ferreira (2009).

[13] The threshold value of 10 that Stock and Yogo (2005) recommend for assessing an instrument's relevance holds for linear models. To run the first-stage, we adjust Petersen (2009)'s code for Tobit models with two-way clustered standard errors, so that the regression can be weighted by the total size of a county's firms. If the standard errors are clustered only at the county (year) level, the F-statistic increases to 9.83 (9.37).

$\widehat{BurnedFrac}_{i,t-1}$ from the second stage. As shown in Column 3 of Table 6, the IV coefficient of wildfire severity is 1.347 with a t-statistic (based on bootstrapped standard errors) of 2.74.

We also check the extent to which our IV coefficient estimate relies on the presence of county fixed effects in the first-stage Tobit model. According to Greene (2004), these may lead to a small downward bias in the variance estimate of the normal error term (even though they are not expected to bias the slope estimators). Therefore, in online Appendix Table 9, we rerun our three-stage estimation after replacing the county fixed effects in the first stage with state fixed effects. The IV coefficient of wildfire severity turns out to be similar and statistically significant significant at the 5% confidence level (i.e., it becomes equal to 1.248 with a t-statistic of 2.07).[14]

For comparison reasons, in Column 1 of Table 6, we show that the OLS estimate of the wildfire severity coefficient is 0.815, and thus very close to our baseline estimate for the whole sample. The higher magnitude of the IV estimate relative to the OLS potentially suggests that any presence of unobservables in Eq. (4) ends up underestimating the true effect of wildfire severity. For example, one such factor may be a contemporaneous environmental attitude in a given county that promotes its sustainability and, at the same time, helps prevent the occurrence of wildfires.

In Column 4 of Table 6, we also estimate the reduced form by replacing in Eq. (4) county i's burned fraction in year t with its corresponding log HDW Index. The estimated coefficient is 32.234 with a t-statistic of 2.22, implying that an increase in a county's HDW Index by 10 percentage points increases its corporate environmental sustainability change by roughly 6 $\left(\approx \frac{32.234 \cdot 10\%}{0.528}\right)$ times relative to the average.

[14] In online Appendix Table 10, we additionally experiment with the more structural methodology of Vella (1993), which involves introducing a control function of the Tobit generalized residuals in Eq. (4). Approximating the control function flexibly with a cubic, quartic or quintic polynomial, we obtain a slightly higher IV estimate, though its t-statistic marginally falls below 2.

4.7.3. Discussion of the exclusion restriction

An important requirement in our IV analysis is the validity of our exclusion restriction, according to which a county's HDW Index affects its local corporate environmental sustainability only through the wildfires that it might cause. To assess whether this assumption is plausible, we run subsample regressions of counties' corporate environmental sustainability change on their log Hot-Dry-Windy Index by conditioning on the absence or presence of a wildfire event. As shown in Columns 1 and 3 of Table 7, the coefficient in both cases is found to be lower than the reduced form estimate and statistically insignificant.

Furthermore, since our three-stage estimation method relies on the nonlinearities of the first-stage Tobit model for identification, we also run subsample regressions of counties' corporate environmental sustainability change on the Tobit fitted values of their wildfire severity based on the HDW Index. In Columns 2 and 4 of the same table, we see again that the respective coefficient estimate is statistically insignificant. Hence, the effect of the HDW Index on the local corporate sustainability through channels other than the one of wildfires is expected to be at worst small and noisy (if not zero).

5. Heterogeneity from the local climate change beliefs or political partisanship

5.1. Climate change Believers versus Deniers

Having shown that wildfire severity has a significant positive effect on the local corporate environmental sustainability, we proceed to test our second hypothesis, according to which the effect is heterogeneous across counties based on their eco-friendly inclination. To this end, we collect a variety of measures of counties' perceptions about climate change from the Yale Climate Opinion Maps - U.S. 2016. All the variables in this data set, which are essentially time series averages of local views from surveys conducted between 2008 and 2016, are strongly correlated. Yet, in terms of definition, the most relevant for us is seems to be the percent of households that believes in anthropogenic climate change (i.e., "thinks that global warming is caused mostly by human activities"), since it reflects the degree to which humans, and hence corporations, are viewed as a determinant factor of climate change.[15]

We therefore divide the counties in our sample into two groups, namely the *Believers* and the *Deniers*, depending on whether the percent of their households that believes in anthropogenic climate change is respectively higher or lower than the median. We then proceed to estimate Eq. (4) separately for each group.

However, before running the subsample regressions, it is important to check that both *Believers* and *Deniers* experience similar wildfires during the sample period. Otherwise, our results will reflect a selection bias. That is, counties with high fractions of believers in anthropogenic climate change might be enhancing more their corporate environmental sustainability, because they are also having more severe wildfires. We thus run at first a balance test in Panel A of Table 8, where we regress a county's wildfire burned fraction in a given year on its *Believer* indicator. Regardless of the controls that are included, the estimated coefficient is small and statistically insignificant, implying that the groups are balanced indeed.

We then show in Panel B that the estimated coefficient of wildfire severity in the *Believer* counties is very close to the baseline estimate in the whole sample and statistically significant (i.e., in Column 2, with all the controls present, it is equal to 0.767 with a t-statistic of 3). On the other hand, the estimated coefficient of wildfire severity in the *Denier* counties is around 50% lower and statistically insignificant (i.e., in Column 4, where all the controls are included, it is equal to 0.417 with a t-statistic of 0.59).

In online Appendix Table 11, we repeat this exercise for two other measures of counties' climate change opinions, namely (i) the percent of households that "is somewhat or very

[15]In our sample, the minimum percent of households that "thinks that global warming is happening", without necessarily believing that it is human-caused, is 52.4%. This means that in all our counties, the majority of the population believes in climate change. Yet, the percent of households that believes that climate change is anthropogenic ranges from 39.2% to 68.4%, with a mean and median value of around 52%.

worried about global warming", and (ii) the percent of households that "discusses global warming occasionally or often with friends and family". Based on the median values of these variables, we distinguish counties into the ones that are *Worried* or *Unconcerned* about climate change, and the ones that are *Discussing* or *Ignoring* climate change. In both cases, the subsample estimation results that we obtain are very similar, providing further empirical support to our conjecture.[16]

5.2. Democrats versus Republicans

In the same spirit, we examine whether the effect of wildfire severity on counties' corporate sustainability change is different based on their political partisanship. Using data from the MIT Election Lab, we divide counties into *Democratic* and *Republican*, depending on which party received the majority of their voters in the most recent presidential election. As one would expect, *Democratic* counties are also likely to be *Believers* of anthropogenic climate change, but not all of them are (i.e., the correlation between these two indicators is 0.7). Moreover, in this sample, there are also counties that flip parties over time.

As before, we start by conducting a balance test in Panel A of Table 9, where we show that a county's Democratic indicator does not predict the severity of wildfires that it experiences. We then rerun the regression based on Eq. (4) in each subsample and report the results in Panel B of Table 9. The coefficient of a county's wildfire burned fraction in the *Democratic* subsample is slightly higher than the baseline estimate in the whole sample and statistically significant (i.e., in Column 2, with full controls, it is equal to 1.028 with a t-statistic of 4). In contrast, in the *Republican* subsample, the coefficient is much smaller and statistically

[16] We also experimented with additional measures such as the percent of households that "thinks that global warming is happening" (without necessarily considering it anthropogenic), (ii) the percent of households that "believes that most scientists think global warming is happening", and (iii) the percent of households that "thinks that global warming will harm future generations a moderate amount or a great deal". Once again, in the subsample where the respective measure was above the median, the estimated coefficient of wildfire severity was similar to the baseline estimate and statistically significant. In contrast, in the below-the-median subsample, the estimated coefficient was always statistically insignificant.

insignificant (i.e., in Column 4, which includes all the controls, it is equal to 0.178 with a t-statistic of 1.51).

To illustrate this heterogeneity graphically, we also plot again the residualized (i.e., the demeaned and detrended) corporate environmental sustainability changes of *Democratic* and *Republican* counties against the fraction of their wildfire burned area in Subfigure 3b. There, we see that the relationship between sustainability changes and wildfire severity is much steeper for *Democratic* counties (as shown by the blue spheres and the corresponding regression line) than for *Republican* counties (as shown by the red spheres and the corresponding regression line). The overlap between the two respective 95% confidence intervals is also small.

Despite the balance between the wildfire severity of Democratic and Republican counties, there is still a noteworthy concern of a sample selection bias from the California counties. In particular (recalling Figure 2) the state of California, which is nowadays considered to be a Democratic stronghold, experiences some of the most severe wildfires of the sample period. To cast more light on this concern, in online Appendix Table 12, we repeat our analysis for the years 2003-2012. By focusing on this subperiod, we are able to limit the selection bias even more, since quite a few California counties which voted for Barack Obama in 2008 had voted for George W. Bush in 2004. The estimated coefficients of wildfire severity in the *Democratic* and *Republican* subsamples are indeed analogous to the ones obtained above for the whole sample period.

6. In search of interim outcomes: The impact on local air enforcement actions from the EPA

Lastly, we extract counties' number of air formal enforcement actions from the Environmental Protection Agency (EPA), as made available by its Enforcement and Compliance History Online (ECHO). These include administrative penalties, field citations, and judicial actions.[17] We extract these data from the ICIS-Air Data Set, i.e., EPA's Integrated Compliance Information System (ICIS) for Clean Air Act Stationary Sources.

The information that we obtain is at the facility-level, so we use EPA's Facility Registry System (FRS) to link each facility with its FIPS county code. This allows us to measure the number of air formal enforcement actions in a given year at the county level by adding them up. For each air formal enforcement action, we do not observe the date of the infraction, but only the settlement entered date. Since it typically takes one year for a facility to settle a case, we assign an air formal enforcement action in year t, if its settlement date is in year $t+1$.

We then focus on county i's annual change in the number of air formal enforcement actions ($\Delta FormActions_{i,t}$), with the understanding that any decrease in this variable indicates or is the result of an increase in its corporate environmental sustainability. In the same spirit, we repeat the above procedure to calculate explicitly county i's annual change in the number of air penalties ($\Delta Penalties_{i,t}$), which are a subset of its air formal enforcement actions. Moreover, we follow similar steps to calculate county i's annual change in the number of air informal enforcement actions ($\Delta InformActions_{i,t}$), which include warning letters and notices of violation sent in year t. The summary statistics of all these changes are presented in Panel E of Table 1.

Next, we reestimate Eq. (4) using each of the aforementioned measures as a dependent variable and present the results in Table 10. As shown in Column 1, when the dependent variable is the local change in the number of air formal enforcement actions, the estimated coefficient of the wildfire severity is equal to -0.710 with a t-statistic of -3.2. The implied economic effect is that a one standard deviation increase in the fraction of a county's burned area decreases its change in the number of air formal enforcement actions by approximately $3(\approx \frac{-0.710 \cdot 0.691}{-0.143})$ times relative to the average.

[17] For details, see Giles, C. (EPA Assistant Administrator), "Informal and Formal Actions Summary of Guidance and Portrayal on EPA Websites", *Environmental Council of the States (ECOS)*, July 1, 2010.

Furthermore, according to Column 2, if the dependent variable is the local change in the number of air penalties, the estimated coefficient of wildfire severity is -1.514 and marginally statistically significant at the 5% confidence level with a t-statistic of -1.96. A one standard deviation increase in the fraction of a county's burned area decreases its change in the number of air penalties by approximately $10(\approx \frac{-1.514 \cdot 0.691}{-0.102})$ times relative to the average. Analogously, in Column 3, where the local change in the number of air informal enforcement actions is a dependent variable, the estimated coefficient of wildfire severity is -1.888 and statistically significant at the 10% confidence level with a t-statistic of -1.88. As with the local change of the air formal enforcement actions, the corresponding economic effect of wildfire severity is a decrease by roughly $3(\approx \frac{-1.888 \cdot 0.691}{-0.412})$ times relative to the average.

Finally, in Column 4, we rerun the regression using as a dependent variable the local change in the number of air stack tests. This allows us to investigate the possibility that the previous decreasing effects are a consequence of an increased leniency from the regulators after a wildfire. Yet, in this case, the coefficient estimate of wildfire severity is found to be positive and statistically insignificant, suggesting that at least the local number of inspections is unaffected.[18]

In online Appendix Table 14, we again examine the heterogeneity of the wildfire severity effect based on counties' climate change beliefs and political partisanship. The scatter plots when the dependent variable is the local change in the number of air formal enforcement actions, for all the counties as well as the separate scatter plots for the Democratic counties and the Republican counties, are depicted in Figure 5. The findings mirror the results that we obtain when we use the local corporate environmental sustainability changes based on the MSCI ESG KLD STATS data in the previous section. The decreasing effect of the wildfire severity on the local change in the number of (i) air formal enforcement actions, (ii)

[18] For each of these variables, we conduct a pre- and post- trends analysis in online Appendix Table 13. Independently of whether we lag or forward them by one or two years, the estimated coefficient of the wildfire severity is always statistically insignificant.

air penalties, or (iii) air informal enforcement actions holds and is, in fact, sharper only in counties that are climate change *Believers* or *Democratic*.

7. Conclusion

In the aftermath of disasters, corporations are typically expected to step up and help counterbalance the damages caused in their communities. Based on that premise, there is a growing literature on the effects of disasters on corporate donations. In this paper, we use wildfires to extend the impact of environmental disasters from corporate giving to the local corporate environmental sustainability.

Using sustainability data from the MSCI ESG KLD STATS database and wildfire data from the MTBS, we find that wildfire severity significantly enhances the growth of the local corporate environmental sustainability. All else being equal, a one standard deviation increase in the fraction of a county's wildfire burned area nearly doubles the annual change of its corporate environmental sustainability relative to the average.

The result is robust to the inclusion of several control variables that might be related to a county's wildfire severity and corporate environmental sustainability. At the same time, there is no impact on the non-environmental aspects of the local corporate sustainability. Our finding is also not driven by pre-trends, neither does it exhibit any post-trends. Notably, the concerns about an omitted variables bias are ameliorated by an instrumental variable analysis that uses the recently developed counties' Hot-Dry-Windy Index.

We further document an important heterogeneity in the response of the local corporate environmental sustainability to the wildfire severity based on the local climate change opinion or the political partisanship. In particular, the response is significant only in counties with a high percent of climate change believers. Moreover, it is significant in Democratic counties, but insignificant in Republican counties. Our conclusions do not change when we consider alternative corporate environmental sustainability data from Morningstar's Sustainalytics, or corporate environmental sustainability outcomes in the interim, such as the local change in the number of air formal enforcement actions from the EPA.

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Table 1
Summary statistics of main variables

This table summarizes the main variables (observed annually) in the sample. Panel A refers to the counties' corporate environmental sustainability change and wildfire severity. $\Delta\overline{EnvSust}$ is the change of a county's corporate environmental sustainability. $BurnedFrac$ is the fraction of a county's wildfire burned area. Panel B refers to the counties' controls. $\log(MarketCap)$ is the log of the total market capitalization of a county's firms. $RATIO$ is the ratio of the total book value of a county's firms over its income. $\log(Pop)$ is the log of a county's population number. $\log(IncPerCap)$ is the log of a county's income per capita. $Unemp$ is a county's unemployment rate. Panel C refers to the counties' corporate non-environmental sustainability changes. $\Delta\overline{DivSust}$ is the change of a county's corporate diversity sustainability. $\Delta\overline{ComSust}$ is the change of a county's corporate community sustainability. $\Delta\overline{EmpSust}$ is the change of a county's corporate employee sustainability. $\Delta\overline{HumSust}$ is the change of a county's corporate human rights sustainability. $\Delta\overline{ProdSust}$ is the change of a county's corporate products sustainability. $\Delta\overline{CGovSust}$ is the change of a county's corporate governance sustainability. Panel D refers to the counties' weather variables. $\log(\overline{HDW})$ is the log of a county's average Hot-Dry-Windy Index. $\log(\overline{HighTMP})$ is the log of a county's average high temperature. $\log(\overline{HighWND})$ is the log of a county's average high wind speed. $\log(\overline{HighVPD})$ is the log of a county's average high vapor pressure deficit. Panel E refers to the counties' changes in the EPA air enforcement actions. $\Delta FormActions$ is a county's change in the number of the EPA air formal enforcement actions. $\Delta Penalties$ is a county's change in the number of the EPA air penalties. $\Delta InformActions$ is a county's change in the number of the EPA air informal enforcement actions. The sample consists of 587 different counties, where the publicly traded firms in the Russell 3000 Index are headquartered during the years 2003-2016. (The weather variables in Panel D are available for a subsample of 443 different counties.)

	Mean	S.D.	Median	Min	Max
Panel A: Local corporate environmental sustainability change and wildfire severity					
$\Delta\overline{EnvSust}$	0.528	7.161	0.000	-30.049	35.000
$BurnedFrac$ (%)	0.087	0.691	0.000	0.000	17.745
Panel B: Controls					
$\log(MarketCap)$	8.112	2.180	7.865	2.493	14.661
$RATIO$	0.464	0.801	0.182	0.000	9.661
$\log(Pop)$	12.425	1.128	12.452	8.240	16.130
$\log(IncPerCap)$	10.594	0.265	10.569	9.690	12.015
$Unemp$ (%)	6.219	2.295	5.700	1.900	17.900
Panel C: Local corporate non-environmental sustainability changes					
$\Delta\overline{\text{DivSust}}$	-0.639	17.977	0.000	-100.000	125.693
$\Delta\overline{\text{ComSust}}$	0.106	15.815	0.000	-196.837	150.000
$\Delta\overline{\text{EmpSust}}$	0.495	11.980	0.000	-75.000	101.429
$\Delta\overline{\text{HumSust}}$	0.322	8.899	0.000	-100.000	100.000
$\Delta\overline{\text{ProdSust}}$	0.506	12.656	0.000	-98.957	100.000
$\Delta\overline{\text{CGovSust}}$	-0.214	22.665	0.000	-116.667	125.000
Panel D: Weather variables					
$\log(\overline{HDW})$	4.369	0.400	4.307	3.276	5.903
$\log(\overline{HighTMP})$	2.947	0.246	2.910	2.003	3.498
$\log(\overline{HighWND})$	1.944	0.167	1.953	1.304	2.488
$\log(\overline{HighVPD})$	2.682	0.336	2.637	1.673	3.873
Panel E: Local changes in the EPA air enforcement actions					
$\Delta FormActions$	-0.143	7.806	0.000	-210	166
$\Delta Penalties$	-0.102	7.156	0.000	-216	163
$\Delta InformActions$	-0.412	21.504	0.000	-392	350

Table 2

Regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area

This table presents the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. Column 1 includes only county and year fixed effects. Column 2 includes all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)
$BurnedFrac$	0.779***	0.800***
	(0.176)	(0.188)
$\log(MarketCap)$		-1.827
		(1.275)
$RATIO$		1.136**
		(0.575)
$\log(Pop)$		9.789
		(12.449)
$\log(IncPerCap)$		-13.657
		(10.970)
$Unemp$		-0.725
		(0.878)
County FE	YES	YES
Year FE	YES	YES
Average number of counties	430	430
Number of years	14	14
R^2	0.426	0.435

Table 3

Regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area and additional controls

This table presents the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area and additional controls. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. Column 1 includes $PrescrFrac_{i,t-1}$, i.e., county i's fraction of area burned by prescribed fires in year $t-1$. Column 2 includes $BurnedFracNeighbor_{i,t-1}$, i.e., the highest fraction of area burned by wildfires in county i's neighboring counties in year $t-1$. Column 3 includes $SearchFire_{i,t-1}$, i.e., county i's average Google search interest in "fires" during the occurrence of any (local or non-local) wildfire in year $t-1$ (the data of which are available only after 2004). All columns include county and year fixed effects and all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)
$BurnedFrac$	0.801***	0.836***	0.898***
	(0.185)	(0.204)	(0.254)
$PrescrFrac$	-1.760*		
	(1.062)		
$BurnedFracNeighbor$		-0.139	
		(0.133)	
$SearchFire$			0.096
			(0.456)
Controls	YES	YES	YES
County FE	YES	YES	YES
Year FE	YES	YES	YES
Average number of counties	430	430	430
Number of years	14	14	13
R^2	0.435	0.435	0.436

Table 4

Placebo regressions of counties' corporate non-environmental sustainability changes on the fraction of their wildfire burned area

This table presents the placebo regressions of counties' corporate non-environmental sustainability changes on the fraction of their wildfire burned area. In Column 1, the dependent variable is $\Delta\overline{DivSust}_{i,t}$, i.e., county i's corporate diversity sustainability change in year t. In Column 2, the dependent variable is $\Delta\overline{ComSust}_{i,t}$, i.e., county i's corporate community sustainability change in year t. In Column 3, the dependent variable is $\Delta\overline{EmpSust}_{i,t}$, i.e., county i's corporate employee sustainability change in year t. In Column 4, the dependent variable is $\Delta\overline{HumSust}_{i,t}$, i.e., county i's corporate human rights sustainability change in year t. In Column 5, the dependent variable is $\Delta\overline{ProdSust}_{i,t}$, i.e., county i's corporate products sustainability change in year t. In Column 6, the dependent variable is $\Delta\overline{CGovSust}_{i,t}$, i.e., county i's corporate governance sustainability change in year t. In all columns, the independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. All columns include county and year fixed effects and all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta\overline{DivSust}$	$\Delta\overline{ComSust}$	$\Delta\overline{EmpSust}$	$\Delta\overline{HumSust}$	$\Delta\overline{ProdSust}$	$\Delta\overline{CGovSust}$
$BurnedFrac$	-0.020	-1.058	0.193	0.128	-0.167	0.704
	(0.388)	(1.029)	(0.294)	(0.396)	(0.270)	(1.001)
Controls	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Average number of counties	430	430	430	430	430	430
Number of years	14	14	14	14	14	14
R^2	0.118	0.377	0.377	0.170	0.152	0.263

Table 5
Regressions of counties' past and future corporate environmental sustainability change on the fraction of their wildfire burned area

This table presents the regressions of counties' past and future corporate environmental sustainability change on the fraction of their wildfire burned area. Panel A refers to counties' one- and two-year lagged corporate environmental sustainability change. In Column 1, the dependent variable is $\Delta\overline{EnvSust}_{i,t-1}$, i.e., county i's corporate environmental sustainability change in year $t-1$. In Column 2, the dependent variable is $\Delta\overline{EnvSust}_{i,t-2}$, i.e., county i's corporate environmental sustainability change in year $t-2$. Panel B refers to counties' one- and two-year forward corporate environmental sustainability change. In Column 1, the dependent variable is $\Delta\overline{EnvSust}_{i,t+1}$, i.e., county i's corporate environmental sustainability change in year $t+1$. In Column 2, the dependent variable is $\Delta\overline{EnvSust}_{i,t+2}$, i.e., county i's corporate environmental sustainability change in year $t+2$. In both panels, the independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. All columns include county and year fixed effects and all county i's controls in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)
Panel A: Regressions of counties' past corporate environmental sustainability change		
	1-year lagged	2-year lagged
$BurnedFrac$	-0.115	-0.346
	(0.304)	(0.385)
Controls	YES	YES
County FE	YES	YES
Year FE	YES	YES
Average number of counties	430	430
Number of years	13	12
R^2	0.461	0.491
Panel B: Regressions of counties' future corporate environmental sustainability change		
	1-year forward	2-year forward
$BurnedFrac$	-0.055	0.141
	(0.231)	(0.307)
Controls	YES	YES
County FE	YES	YES
Year FE	YES	YES
Average number of counties	430	430
Number of years	13	12
R^2	0.410	0.444

Table 6

IV regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area using the log of their Hot-Dry-Windy Index as an instrument

This table presents the IV regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area using the log of their Hot-Dry-Windy Index as an instrument. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. Column 1 shows the OLS regression. Columns 2, 3, and 4 show the IV regressions. The instrument is $\log(\overline{HDW}_{i,t-1})$, i.e., the log of county i's average Hot-Dry-Windy Index in year $t-1$. To account for the censoring of $BurnedFrac_{i,t-1}$, a three-stage estimation method is applied. The first stage is a Tobit regression of $BurnedFrac_{i,t-1}$ on $\log(\overline{HDW}_{i,t-1})$, shown in Column 2. The second stage is a linear regression of $BurnedFrac_{i,t-1}$ on the nonlinear fitted values $\widehat{BurnedFrac}^{Tobit}_{i,t-1}$ from the first stage. The third stage is a linear regression of $\Delta\overline{EnvSust}_{i,t}$ on the linear fitted values $\widehat{BurnedFrac}_{i,t-1}$ from the second stage, shown in Column 3. Column 4 shows the reduced form, where $BurnedFrac_{i,t-1}$ is replaced by $\log(\overline{HDW}_{i,t-1})$. All columns include county and year fixed effects and all county i's controls in year $t-1$. The logs of county i's average high temperature $\big(\log(\overline{HighTMP}_{i,t-1})\big)$, average high wind speed $\big(\log(\overline{HighWND}_{i,t-1})\big)$, and average high vapor pressure deficit $\big(\log(\overline{HighVPD}_{i,t-1})\big)$ in year $t-1$ are also included as controls. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and (for Columns 1, 2 and 4) the two-way clustered standard errors at the county and year level or (for Column 3) the bootstrapped standard errors (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)	(4)
	OLS	IV regressions		
		1st stage Tobit	3rd stage	Reduced form
$BurnedFrac$	0.815***		1.347***	
	(0.174)		(0.492)	
$\log(\overline{HDW})$		32.130***		32.234**
		(11.134)		(14.537)
$\log(\overline{HighTMP})$	-27.235	6.691	-26.653	-22.112
	(23.579)	(17.018)	(20.779)	(20.586)
$\log(\overline{HighWND})$	-13.534	-21.209**	-13.849	-26.596**
	(9.055)	(10.514)	(14.980)	(13.279)
$\log(\overline{HighVPD})$	20.384	-30.908**	20.079	-17.155
	(14.301)	(14.292)	(12.392)	(11.691)
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	289	289	289	289
Number of years	14	14	14	14
R^2	0.448	0.522 (pseudo)	0.449	0.452

Table 7

Exclusion restriction analysis: The impact of the Hot-Dry-Windy Index on counties' corporate environmental sustainability change given the absence or presence of a wildfire

This table presents the regressions of counties' corporate environmental sustainability change on the log of their Hot-Dry-Windy Index or Tobit fitted values of their wildfire severity on it, given the absence or presence of a wildfire event. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. In Columns 1 and 3, the independent variable is $\log(\overline{HDW}_{i,t-1})$, i.e., the log of county i's average Hot-Dry-Windy Index in year $t-1$. In Columns 2 and 4, the independent variable is $\widehat{BurnedFrac}^{Tobit}_{i,t-1}$, i.e., the fitted values from the first-stage Tobit regression of county i's fraction of area burned by wildfires in year $t-1$ (denoted by $BurnedFrac_{i,t-1}$) on $\log(\overline{HDW}_{i,t-1})$. In Columns 1 and 2, only counties that do not experience a wildfire in year $t-1$ (i.e., $BurnedFrac_{i,t-1} = 0$) are considered. In Columns 3 and 4, only counties that experience a wildfire in year $t-1$ (i.e., $BurnedFrac_{i,t-1} > 0$) are considered. All columns include county and year fixed effects and all county i's controls in year $t-1$. The logs of county i's average high temperature $\left(\log(\overline{HighTMP}_{i,t-1})\right)$, average high wind speed $\left(\log(\overline{HighWND}_{i,t-1})\right)$, and average high vapor pressure deficit $\left(\log(\overline{HighVPD}_{i,t-1})\right)$ in year $t-1$ are also included as controls. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)	(4)
	$BurnedFrac = 0$		$BurnedFrac > 0$	
$\log(\overline{HDW})$	25.887		-10.591	
	(19.260)		(31.881)	
$\widehat{BurnedFrac}^{Tobit}$		1.548		0.585
		(1.422)		(1.564)
$\log(\overline{HighTMP})$	-15.525	-18.117	26.885	47.919
	(24.832)	(25.956)	(62.581)	(55.540)
$\log(\overline{HighWND})$	-25.953	-15.531	50.191	37.545
	(15.977)	(9.658)	(35.833)	(24.408)
$\log(\overline{HighVPD})$	-15.525	13.607	-9.808	-29.101*
	(15.212)	(16.071)	(41.930)	(17.409)
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	260	260	29	29
Number of years	14	14	14	14
R^2	0.446	0.442	0.779	0.780

Table 8
Subsample analysis based on counties' anthropogenic climate change opinion

This table presents the subsample analysis based on counties' anthropogenic climate change opinion. Panel A shows the balance test, i.e., the regressions of counties' fraction of wildfire burned area on the anthropogenic climate change believer indicator variable. The dependent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. The independent variable is $Believer_i$, i.e., an indicator variable that is equal to one if the percent of households that believes in anthropogenic climate change in county i is above the median. Column 1 includes only year fixed effects. Column 2 adds county i's controls in year $t-1$. Panel B shows the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area, when counties are split into two subsamples based on their anthropogenic climate change opinion. Columns 1 and 2 refer to the *Believers*, i.e., counties where the percent of households that believes in anthropogenic climate change is above the median. Columns 3 and 4 refer to the *Deniers*, i.e., counties where the percent of households that believes in anthropogenic climate change is below the median. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. Columns 1 and 3 include only county and year fixed effects. Columns 2 and 4 include all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)	(4)
Panel A (Balance test): Regressions of counties' fraction of wildfire burned area on the anthropogenic climate change believer indicator variable				
Believer	0.082	-0.128		
	(0.066)	(0.106)		
Controls	NO	YES		
Year FE	YES	YES		
Average number of counties	430	430		
Number of years	14	14		
R^2	0.024	0.073		
Panel B: Regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in subsamples based on their anthropogenic climate change opinion				
	Believers		*Deniers*	
BurnedFrac	0.746***	0.767***	0.392	0.417
	(0.165)	(0.256)	(0.663)	(0.710)
Controls	NO	YES	NO	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	215	215	215	215
Number of years	14	14	14	14
R^2	0.482	0.492	0.258	0.273

Table 9
Subsample analysis based on counties' political partisanship

This table presents the subsample analysis based on counties' political partisanship. Panel A shows the balance test, i.e., the regressions of counties' fraction of wildfire burned area on the Democratic indicator variable. The dependent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. The independent variable is $Democratic_{i,t-1}$, i.e., an indicator variable that is equal to one if the majority of voters in county i are Democrats in year $t-1$ (based on the most recent presidential election). Column 1 includes only county and year fixed effects. Column 2 includes all county i's controls in year $t-1$. Panel B shows the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area, when counties are split into two subsamples based on their political partisanship. Columns 1 and 2 refer to the *Democratic* counties. Columns 3 and 4 refer to the *Republican* counties. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. Columns 1 and 3 include only county and year fixed effects. Columns 2 and 4 include all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)	(4)
Panel A (Balance test): Regressions of counties' fraction of wildfire burned area on the Democratic indicator variable				
Democratic	-0.278	-0.276		
	(0.211)	(0.230)		
Controls	NO	YES		
County FE	YES	YES		
Year FE	YES	YES		
Average number of counties	430	430		
Number of years	14	14		
R^2	0.269	0.269		
Panel B: Regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in subsamples based on their political partisanship				
	Democratic		*Republican*	
BurnedFrac	1.041***	1.028***	0.208	0.178
	(0.188)	(0.257)	(0.144)	(0.118)
Controls	NO	YES	NO	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	211	211	219	219
Number of years	14	14	14	14
R^2	0.498	0.510	0.221	0.230

Table 10

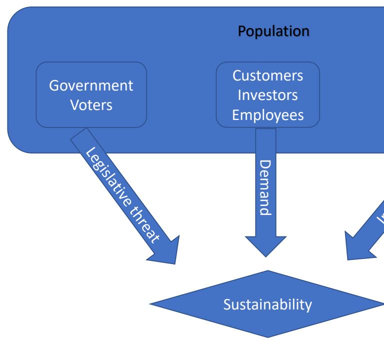
Regressions of counties' change in the number of (i) air formal enforcement actions, (ii) air penalties, (iii) air informal enforcement actions, and (iv) air stack tests from the EPA on the fraction of their wildfire burned area

This table presents the regressions of counties' change in the number of (i) air formal enforcement actions, (ii) air penalties, (iii) air informal enforcement actions, and (iv) air stack tests from the EPA on the fraction of their wildfire burned area. In Column 1, the dependent variable is $\Delta FormActions_{i,t}$, i.e., county i's change in the number of air formal enforcement actions in year t. In Column 2, the dependent variable is $\Delta Penalties_{i,t}$, i.e., county i's change in the number of air penalties in year t. In Columns 3, the dependent variable is $\Delta InformActions_{i,t}$, i.e., county i's change in the number of air informal enforcement actions in year t. In Columns 4, the dependent variable is $\Delta StackTests_{i,t}$, i.e., county i's change in the number of air stack tests in year t. In all columns, the independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. All columns include county and year fixed effects and all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

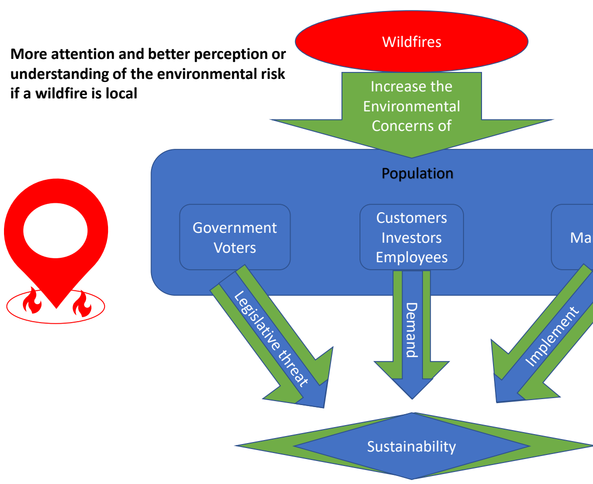
	(1)	(2)	(3)	(4)
	$\Delta FormActions$	$\Delta Penalties$	$\Delta InformActions$	$\Delta StackTests$
$BurnedFrac$	-0.710***	-1.514**	-1.888*	8.105
	(0.222)	(0.771)	(1.006)	(7.736)
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	430	430	430	430
Number of years	14	14	14	14
R^2	0.063	0.073	0.087	0.090

Fig. 1. The framework for the effect of wildfires on the local corporate environmental sustainability change. Subfigure 1a shows the normal framework of why firms engage in sustainability. Subfigure 1b shows the framework for *Hypothesis 1*: "Wildfires increase the corporate environmental sustainability in the counties where they occur." Subfigure 1c shows the framework for *Hypothesis 2*: "The effect of wildfires on the corporate environmental sustainability in a county depends on its communal beliefs about climate change and its political partisanship".

(a) Normal framework



(b) Hypothesis 1 framework



(c) Hypothesis 2 framework

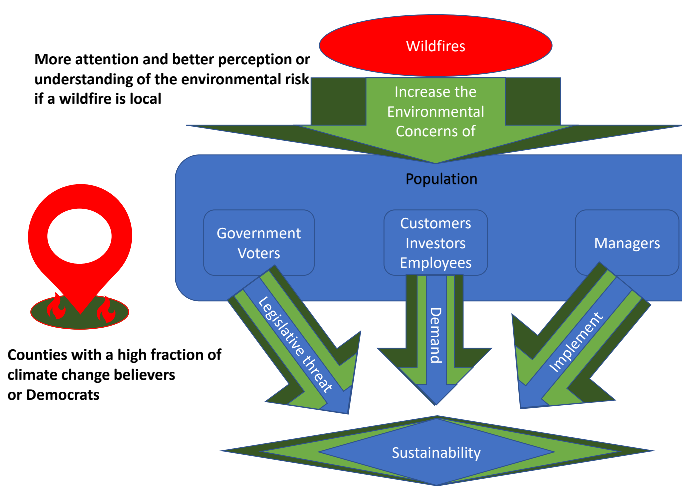


Fig. 2. The map of counties' average fraction of wildfire burned area during the sample period 2003-2016. This figure depicts the geographical distribution of the time-series average of the fraction of the wildfire burned area in each U.S. county. Counties that do not experience any wildfire are shown with white color. Black dots indicate the ZIP-codes of the headquarters of the publicly traded firms in the Russell 3000 Index.

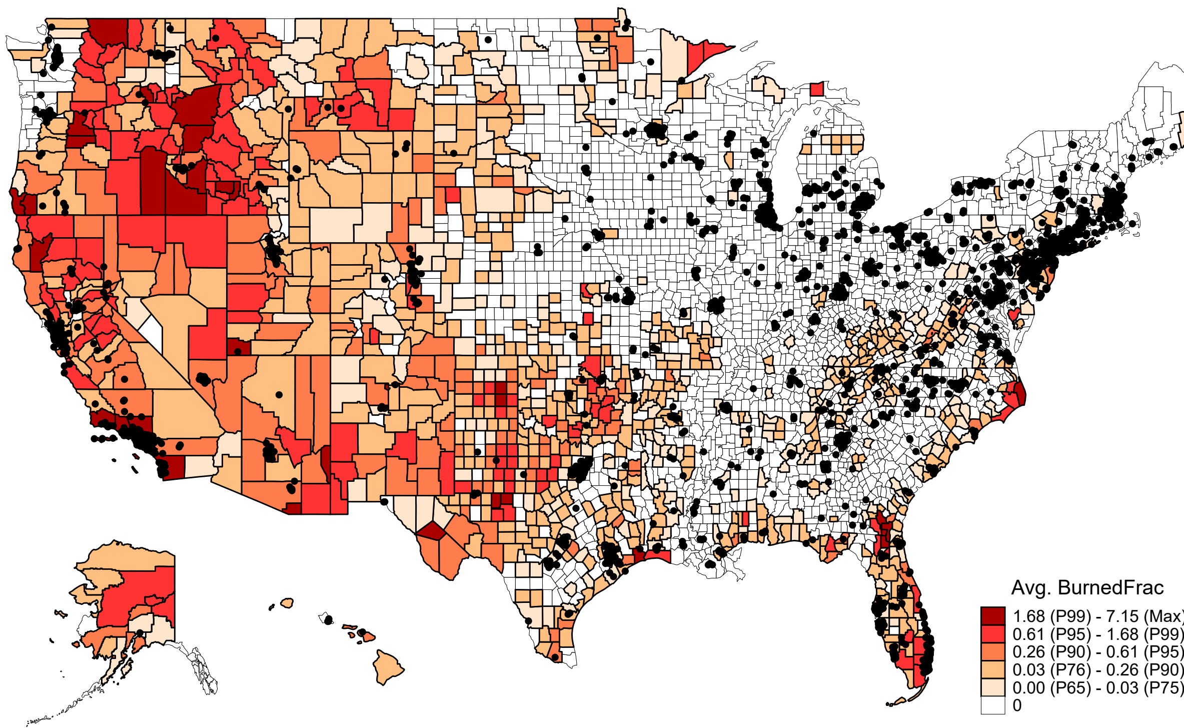
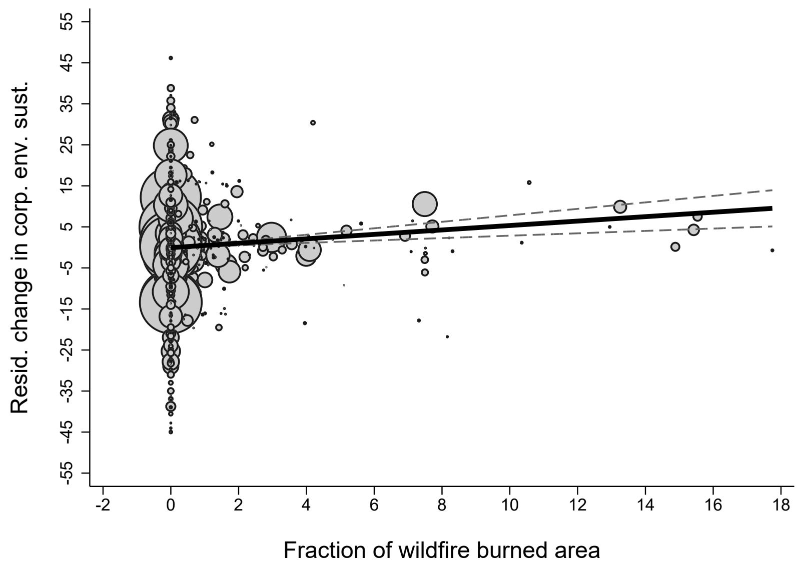


Fig. 3. Scatter plots of counties' residualized corporate environmental sustainability change on the fraction of their wildfire burned area. The residuals are obtained from regressions that include county and year fixed effects, and are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. Subfigure 3a shows the scatter plot for all the counties in the sample. Subfigure 3b distinguishes between the scatter plot of the Democratic counties (depicted with blue spheres) and the scatter plot of the Republican counties (depicted with red spheres). Solid lines depict the linear fit prediction plots. Dashed lines depict the corresponding 95% confidence intervals.

(a) All counties



(b) Democratic (blue) vs. Republican (red) counties

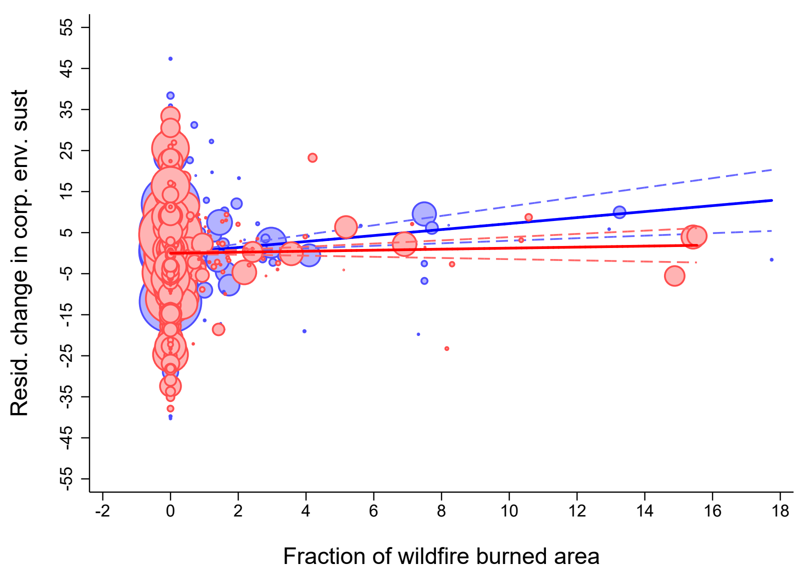


Fig. 4. Regression coefficient estimates of counties' past, current, and future corporate environmental sustainability change on the fraction of their wildfire burned area. The dependent variables are $\Delta\overline{EnvSust}_{i,t-2}$, $\Delta\overline{EnvSust}_{i,t-1}$, $\Delta\overline{EnvSust}_{i,t}$, $\Delta\overline{EnvSust}_{i,t+1}$, and $\Delta\overline{EnvSust}_{i,t+2}$, i.e., county i's corporate environmental sustainability change in year $t-2$, $t-1$, t, $t+1$, and $t+2$, respectively. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. The regressions include county and year fixed effects and all county i's controls in year $t-1$, and are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. White dashes depict the point estimates. Solid black lines depict the corresponding 95% confidence intervals based on two-way clustered standard errors at the county and year level.

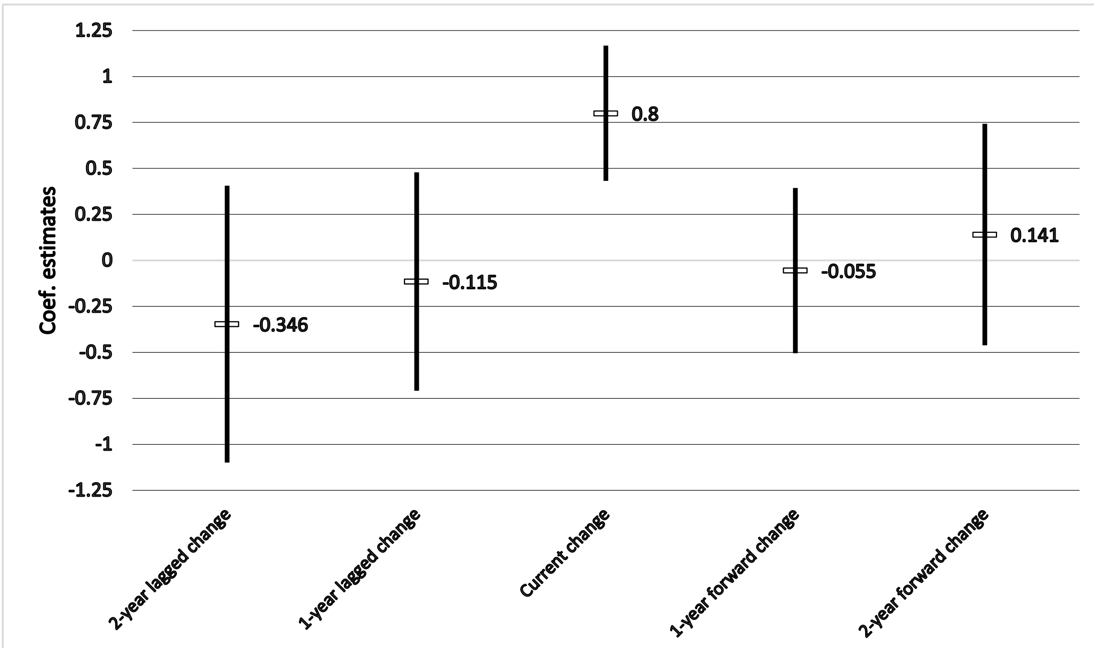
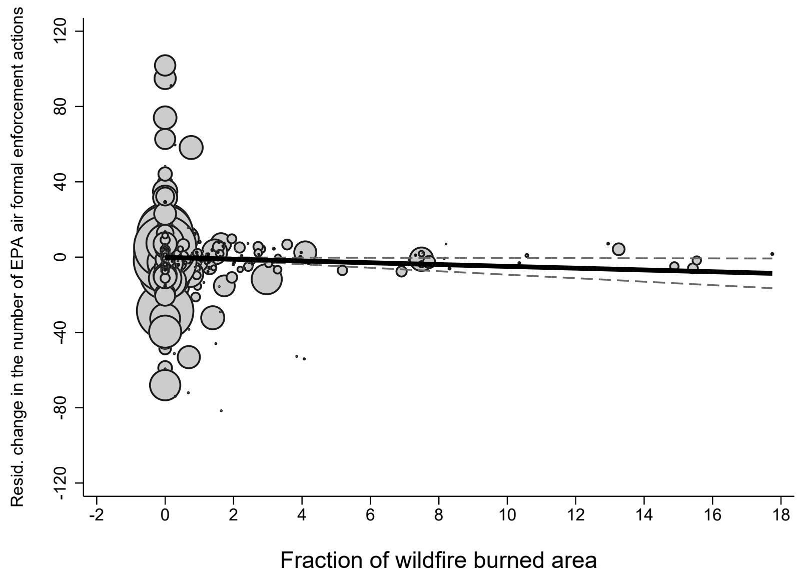
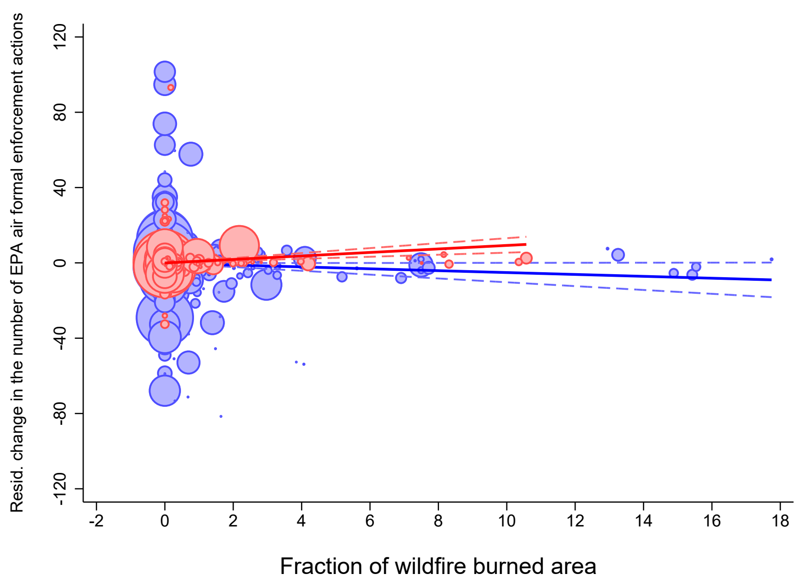


Fig. 5. Scatter plots of counties' residualized change in the number of EPA air formal enforcement actions on the fraction of their wildfire burned area. The residuals are obtained from regressions that include county and year fixed effects, and are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. Subfigure 5a shows the scatter plot for all the counties in the sample. Subfigure 5b distinguishes between the scatter plot of the Democratic counties (depicted with blue spheres) and the scatter plot of the Republican counties (depicted with red spheres). Solid lines depict the linear fit prediction plots. Dashed lines depict the corresponding 95% confidence intervals.

(a) All counties



(b) Democratic (blue) vs. Republican (red) counties



Online Appendix

Online Appendix Table 1

The full list of strengths and concerns of corporate environmental sustainability

This table presents the full list of strengths and concerns of corporate environmental sustainability in the MSCI ESG KLD STATS database. Panel A (B) refers to the strengths (concerns) of corporate environmental sustainability. Each item is enumerated in Column 1 and labeled in Column 2.

(1)	(2)
#	Label
Panel A: Strengths of corporate environmental sustainability	
1	Environmental Opportunities in Clean Tech (Beneficial Products and Services)
2	Pollution & Waste - Toxic Emissions and Waste (Pollution Prevention)
3	Pollution & Waste - Packaging Materials & Waste (Recycling)
4	Climate Change - Carbon Emissions (Clean Energy)
5	Environmental Communications
6	Property, Plant, Equipment
7	Environmental Management Systems (Management Systems Strength)
8	Natural Capital - Water Stress
9	Natural Capital - Biodiversity & Land Use
10	Natural Capital - Raw Material Sourcing
11	Climate Change - Financing Environmental Impact
12	Environmental Opportunities - Opportunities in Green Building
13	Environmental Opportunities - Opportunities in Renewable Energy
14	Pollution & Waste - Electronic Waste
15	Climate Change - Energy Efficiency
16	Climate Change - Product Carbon Footprint
17	Climate Change - Climate Change Vulnerability
18	Environment - Other Strengths
Panel B: Concerns of corporate environmental sustainability	
1	Hazardous Waste
2	Regulatory Compliance (Regulatory Problems)
3	Ozone Depleting Chemicals
4	Toxic Emissions and Waste (Substantial Emissions)
5	Agriculture Chemicals
6	Energy & Climate Change
7	Impact of Products and Services
8	Biodiversity & Land Use
9	Operational Waste (Non-Hazardous)
10	Supply Chain Management
11	Water Stress (Water Management)
12	Environment - Other Concerns

Online Appendix Table 2

Regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area for alternative measures of firms' size

This table presents the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area for alternative measures of firms' size. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. In Panel A (B), it is calculated using firms' market capitalization (total assets) as their size. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. Column 1 includes only county and year fixed effects. Column 2 includes all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their market capitalization in Panel A and their total assets in Panel B) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)
Panel A: Firms' size measured by their market capitalization		
$BurnedFrac$	0.752***	0.743***
	(0.188)	(0.175)
$\log(MarketCap)$		-2.246*
		(1.332)
$RATIO$		0.498
		(0.515)
$\log(Pop)$		-0.039
		(16.078)
$\log(IncPerCap)$		-13.420
		(13.367)
$Unemp$		-0.300
		(0.654)
County FE	YES	YES
Year FE	YES	YES
Average number of counties	430	430
Number of years	14	14
R^2	0.374	0.381
Panel B: Firms' size measured by their total assets		
$BurnedFrac$	0.690***	0.729***
	(0.192)	(0.239)
$\log(MarketCap)$		-2.970
		(1.858)
$RATIO$		2.242*
		(1.268)
$\log(Pop)$		-0.080
		(12.384)
$\log(IncPerCap)$		-6.129
		(11.903)
$Unemp$		-1.012
		(0.960)
County FE	YES	YES
Year FE	YES	YES
Average number of counties	430	430
Number of years	14	14
R^2	0.451	0.464

Online Appendix Table 3

Summary statistics and regressions of counties' additional controls on the fraction of their wildfire burned area

This table presents the summary statistics and regressions of counties' additional controls on the fraction of their own wildfire burned area. Panel A shows the summary statistics. Panel B shows the regressions. In Column 1, the dependent variable is $PrescrFrac_{i,t}$, i.e., county i's fraction of area burned by prescribed fires in year t. In Column 2, the dependent variable is $BurnedFracNeighbor_{i,t}$, i.e., the highest fraction of area burned by wildfires in county i's neighboring counties in year t. In Column 3, the dependent variable is $SearchFire_{i,t}$, i.e., county i's average Google search interest in "fires" during the occurrence of any (local or non-local) wildfire in year t (the data of which are available only after 2004). All columns include county and year fixed effects. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

Panel A: Summary statistics of counties' additional controls

	Mean	S.D.	Median	Min	Max
$PrescrFrac$	0.037	0.370	0	0	15.783
$BurnedFracNeighbor$	0.348	1.458	0	0	22.764
$SearchIndex$	15.769	6.883	14.413	4.718	55.418

Panel B: Regressions of counties' additional controls on their wildfire severity

	(1) $PrescrFrac$	(2) $BurnedFracNeighbor$	(3) $SearchFire$
$BurnedFrac$	-0.011	0.439***	0.383***
	(0.008)	(0.154)	(0.120)
County FE	YES	YES	YES
Year FE	YES	YES	YES
Average number of counties	430	430	430
Number of years	14	14	13
R^2	0.349	0.327	0.936

Online Appendix Table 4

Regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in subsamples that drop observations with very high wildfire severity or counties in California

This table presents the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in subsamples that drop observations with very high wildfire severity or counties in California. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. In Column 1, only observations with a wildfire burned fraction less than 10% (i.e., $BurnedFrac_{i,t-1} < 10$) are considered. In Column 2, only counties outside the state of California are considered. Both columns include county and year fixed effects and all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)
	$BurnedFrac$<10	No CA counties
$BurnedFrac$	1.133***	0.809**
	(0.200)	(0.379)
log($MarketCap$)	-1.863	-1.912*
	(1.223)	(1.062)
$RATIO$	1.146**	1.508***
	(0.553)	(0.373)
log(Pop)	9.822	17.267
	(11.938)	(10.677)
log($IncPerCap$)	-13.500	-7.158
	(10.544)	(8.269)
$Unemp$	-0.757	-1.014
	(0.834)	(0.814)
County FE	YES	YES
Year FE	YES	YES
Average number of counties	430	396
Number of years	14	14
R^2	0.435	0.424

Online Appendix Table 5

Regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in subsamples that drop counties with low fraction of forest area

This table presents the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in subsamples that drop counties with low fraction of forest area. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. In Panel A, only counties with a fraction of forest area above the 10% percentile are considered. In Panel B, only counties with a fraction of forest area above the 25% percentile are considered. Column 1 includes only county and year fixed effects. Column 2 includes all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)
Panel A: Dropping counties whose fraction of forest area is less than the 10% percentile		
$BurnedFrac$	0.772***	0.801***
	(0.178)	(0.175)
log($MarketCap$)		-1.735
		(1.681)
$RATIO$		1.110*
		(0.641)
log(Pop)		12.263
		(13.937)
log($IncPerCap$)		-12.818
		(11.917)
$Unemp$		-0.607
		(0.888)
County FE	YES	YES
Year FE	YES	YES
Average number of counties	379	379
Number of years	14	14
R^2	0.439	0.447
Panel B: Dropping counties whose fraction of forest area is less than the 25% percentile		
$BurnedFrac$	0.848***	0.885***
	(0.197)	(0.204)
log($MarketCap$)		-1.918
		(1.704)
$RATIO$		1.178*
		(0.636)
log(Pop)		12.907
		(14.282)
log($IncPerCap$)		-12.899
		(12.232)
$Unemp$		-0.636
		(0.892)
County FE	YES	YES
Year FE	YES	YES
Average number of counties	363	363
Number of years	14	14
R^2	0.444	0.453

Online Appendix Table 6

Regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in balanced panels

This table presents the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in balanced panels. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. In Panel A, the balanced panel consists of counties that are observed in all the years of the sample period. In Panel B, the balanced panel consists of counties where companies that are observed in all the years of the sample period are headquartered. Column 1 includes only county and year fixed effects. Column 2 includes all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)
Panel A: Balanced panel of counties that are observed during the whole sample period		
$BurnedFrac$	0.782***	0.804***
	(0.172)	(0.185)
$\log(MarketCap)$		-1.934
		(1.335)
$RATIO$		1.117*
		(0.590)
$\log(Pop)$		10.412
		(12.660)
$\log(IncPerCap)$		-13.935
		(10.950)
$Unemp$		-0.744
		(0.902)
County FE	YES	YES
Year FE	YES	YES
Number of counties	308	308
Number of years	14	14
R^2	0.428	0.437
Panel B: Balanced panel of counties where companies that are observed during the whole sample period are headquartered		
$BurnedFrac$	1.051***	1.064***
	(0.390)	(0.407)
$\log(MarketCap)$		-1.692
		(2.435)
$RATIO$		-0.287
		(2.387)
$\log(Pop)$		7.750
		(12.979)
$\log(IncPerCap)$		-18.250
		(13.912)
$Unemp$		-1.077
		(0.987)
County FE	YES	YES
Year FE	YES	YES
Number of counties	292	292
Number of years	14	14
R^2	0.441	0.448

Online Appendix Table 7

Regressions of counties' corporate environmental sustainability change on alternative measures of wildfire severity

This table presents the regressions of counties' corporate environmental sustainability change on alternative measures of wildfire severity. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. In Panel A, the independent variable is $FireDum_{i,t-1}$, i.e., an indicator variable that is equal to one if county i experiences a wildfire in year $t-1$. In Panel B, the independent variable is $\log(BurnedAcr_{i,t-1}+1)$, i.e., the log of the acres of county i's area burned by wildfires in year $t-1$ plus one. Column 1 includes only county and year fixed effects. Column 2 includes all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). See Table 1 for sample characteristics and variable definitions.

	(1)	(2)
Panel A: Regressions on the wildfire occurrence indicator variable		
$FireDum$	3.393***	3.667***
	(0.776)	(0.977)
$\log(MarketCap)$		-1.993
		(1.293)
$RATIO$		1.284***
		(0.493)
$\log(Pop)$		12.026
		(12.221)
$\log(IncPerCap)$		-11.858
		(10.351)
$Unemp$		-0.738
		(0.919)
County FE	YES	YES
Year FE	YES	YES
Average number of counties	430	430
Number of years	14	14
R^2	0.427	0.436
Panel B: Regressions on the log of the acres of the wildfire burned area plus one		
$\log(BurnedAcr+1)$	0.225***	0.246***
	(0.045)	(0.058)
$\log(MarketCap)$		-2.187*
		(1.270)
$RATIO$		1.329***
		(0.495)
$\log(Pop)$		11.903
		(12.219)
$\log(IncPerCap)$		-12.230
		(10.246)
$Unemp$		-0.869
		(0.857)
County FE	YES	YES
Year FE	YES	YES
Average number of counties	430	430
Number of years	14	14
R^2	0.420	0.430

Online Appendix Table 8

Robustness to alternative corporate sustainability data from Sustainalytics

This table presents the robustness using alternative corporate sustainability data from Sustainalytics. The sample is an unbalanced panel of 248 different counties, where the publicly traded firms in the Russell 1000 Index are headquartered during the years 2010-2017. Panel A shows the summary statistics. $\Delta\overline{Escore}$ is a county's change in the corporate environmental sustainability. $\Delta\overline{Sscore}$ is a county's change in the corporate social sustainability. $\Delta\overline{Gscore}_{i,t}$ is a county's change in the corporate governance sustainability. $BurnedFrac$ is the fraction of a county's wildfire burned area. Panel B shows the regressions of counties' corporate sustainability changes on the fraction of their wildfire burned area. Panel C shows the the regressions of counties' past and future corporate environmental sustainability change. Panel D shows the subsample regressions of counties' corporate environmental sustainability change based on their climate change opinion or political partisanship. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

Panel A: Summary statistics of the local corporate sustainability changes and wildfire severity

	Mean	S.D.	Median	Min	Max
$\Delta\overline{Escore}$	0.672	2.868	0.000	-7.150	13.287
$\Delta\overline{Sscore}$	0.432	2.924	0.000	-9.000	12.000
$\Delta\overline{Gscore}$	0.262	2.419	0.000	-8.000	9.986
BurnedFrac (%)	0.062	0.475	0.000	0.000	10.572

Panel B: Regressions of counties' corporate sustainability changes on their wildfire burned area

	(1)	(2)	(3)	(4)
	$\Delta\overline{Escore}$		$\Delta\overline{Sscore}$	$\Delta\overline{Gscore}$
$BurnedFrac$	0.572***	0.633***	0.144	0.096
	(0.121)	(0.140)	(0.338)	(0.603)
Controls	NO	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	223	223	223	223
Number of years	8	8	8	8
R^2	0.348	0.361	0.369	0.201

Panel C: Regressions of counties' past & future change corporate environmental sustainability change ($\Delta\overline{Escore}$)

	1-year lagged	2-year lagged	1-year forward	2-year forward
$BurnedFrac$	-0.015	-0.493	-0.407	-0.178
	(0.099)	(0.683)	(0.643)	(0.361)
Controls	NO	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	223	223	223	223
Number of years	7	6	7	6
R^2	0.322	0.357	0.445	0.309

Panel D: Subsample regressions of counties' corporate environmental sustainability change ($\Delta\overline{Escore}$)

	Climate change opinion		Political partisanship	
	Believers	Deniers	Democratic	Republican
$BurnedFrac$	0.748**	0.258	0.772***	0.105
	(0.350)	(0.355)	(0.282)	(0.739)
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	111	112	109	114
Number of years	8	8	8	8
R^2	0.398	0.384	0.407	0.339

Online Appendix Table 9

IV regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area using the log of their Hot-Dry-Windy Index as an instrument with state (instead of county) fixed effects in the first-stage Tobit model

This table presents the IV regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area using the log of their Hot-Dry-Windy Index as an instrument with state (instead of county) fixed effects in the first-stage Tobit model. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. The instrument is $\log(\overline{HDW}_{i,t-1})$, i.e., the log of county i's average Hot-Dry-Windy Index in year $t-1$. To account for the censoring of $BurnedFrac_{i,t-1}$, a three-stage estimation method is applied. The first stage is a Tobit regression of $BurnedFrac_{i,t-1}$ on $\log(\overline{HDW}_{i,t-1})$, shown in Column 1. The second stage is a linear regression of $BurnedFrac_{i,t-1}$ on the nonlinear fitted values $\widehat{BurnedFrac}^{Tobit}_{i,t-1}$ from the first stage. The third stage is a linear regression of $\Delta\overline{EnvSust}_{i,t}$ on the linear fitted values $\widehat{BurnedFrac}_{i,t-1}$ from the second stage, shown in Column 2. Column 1 includes state fixed effects. Column 2 includes county fixed effects. All columns include year fixed effects and all county i's controls in year $t-1$. The logs of county i's average high temperature $\left(\log(\overline{HighTMP}_{i,t-1})\right)$, average high wind speed $\left(\log(\overline{HighWND}_{i,t-1})\right)$, and average high vapor pressure deficit $\left(\log(\overline{HighVPD}_{i,t-1})\right)$ in year $t-1$ are also included as controls. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and (for Columns 1) the two-way clustered standard errors at the county and year level or (for Column 2) the bootstrapped standard errors (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1) 1st stage Tobit	(2) 3rd stage
$BurnedFrac$		1.248**
		(0.603)
$\log(\overline{HDW})$	22.831***	
	(7.147)	
$\log(\overline{HighTMP})$	23.276**	-26.762
	(9.822)	(20.692)
$\log(\overline{HighWND})$	-14.368***	-13.790
	(4.880)	(14.851)
$\log(\overline{HighVPD})$	-29.596***	20.136
	(8.984)	(12.422)
Controls	YES	YES
State FE	YES	NO
County FE	NO	YES
Year FE	YES	YES
Average number of counties	289	289
Number of years	14	14
R^2	0.429 (pseudo)	0.449

Online Appendix Table 10

IV regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area using the log of their Hot-Dry-Windy Index as an instrument and a control function of the generalized residual from the first-stage Tobit model

This table presents the IV regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area using the log of their Hot-Dry-Windy Index as an instrument and a control function of the generalized residual from the first-stage Tobit model. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. The instrument is $\log(\overline{HDW}_{i,t-1})$, i.e., the log of county i's average Hot-Dry-Windy Index in year $t-1$. The approximation of the control function is cubic in Column 1, quartic in Column 2, and quintic in Column 3. All columns include county and year fixed effects and all county i's controls in year $t-1$. The logs of county i's average high temperature $\left(\log(\overline{HighTMP}_{i,t-1})\right)$, average high wind speed $\left(\log(\overline{HighWND}_{i,t-1})\right)$, and average high vapor pressure deficit $\left(\log(\overline{HighVPD}_{i,t-1})\right)$ in year $t-1$ are also included as controls. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the bootstrapped standard errors (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1) Cubic CF	(2) Quartic CF	(3) Quintic CF
$BurnedFrac$	1.449**	1.536*	1.556*
	(0.730)	(0.814)	(0.831)
$\log(\overline{HDW})$			
$\log(\overline{HighTMP})$	-24.446	-27.196	-27.469
	(23.626)	(26.699)	(26.977)
$\log(\overline{HighWND})$	-8.180	-7.112	-7.066
	(13.358)	(13.670)	(13.710)
$\log(\overline{HighVPD})$	13.662	13.027	12.943
	(11.140)	(11.704)	(11.768)
Controls	YES	YES	YES
County FE	YES	YES	YES
Year FE	YES	YES	YES
Average number of counties	289	289	289
Number of years	14	14	14
R^2	0.454	0.455	0.456

Online Appendix Table 11

Subsample analysis based on alternative measures of counties' climate change opinion

This table presents the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in subsamples based on alternative measures of their climate change opinion. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. In Panel A, counties are split into two subsamples based on their climate change concerns. Columns 1 and 2 refer to the *Worried* counties, i.e., counties where the percent of households that is worried about climate change is above the median. Columns 3 and 4 refer to the *Unconcerned* counties, i.e., counties where the percent of households that is worried about climate change is below the median. In Panel B, counties are split into two subsamples based on their climate change discussions. Columns 1 and 2 refer to the *Discussing* counties, i.e., counties where the percent of households that discusses climate change with family and friends is above the median. Columns 3 and 4 refer to the *Ignoring* counties, i.e., counties where the percent of households that discusses climate change with family and friends is below the median. Columns 1 and 3 include only county and year fixed effects. Columns 2 and 4 include all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)	(4)
Panel A: Subsample regressions based on counties' climate change concerns				
	Worried		*Unconcerned*	
$BurnedFrac$	0.758***	0.780***	0.519	0.448
	(0.154)	(0.259)	(0.859)	(0.806)
Controls	NO	YES	NO	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	215	215	215	215
Number of years	14	14	14	14
R^2	0.490	0.501	0.217	0.240
Panel B: Subsample regressions based on counties' climate change discussions				
	Discussing		*Ignoring*	
$BurnedFrac$	0.774***	0.799***	0.208	0.164
	(0.161)	(0.267)	(0.658)	(0.608)
Controls	NO	YES	NO	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	215	215	215	215
Number of years	14	14	14	14
R^2	0.494	0.506	0.238	0.261

Online Appendix Table 12

Subsample analysis based on counties' political partisanship in the years before 2012

This table presents the subsample analysis based on counties' political partisanship in the years before 2012. Panel A shows the balance test, i.e., the regressions of counties' fraction of wildfire burned area on the Democratic indicator variable. The dependent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. The independent variable is $Democratic_{i,t-1}$, i.e., an indicator variable that is equal to one if the majority of voters in county i are Democrats in year $t-1$ (based on the most recent presidential election). Columns 1 and 2 refer to the years before 2012. Columns 3 and 4 refer to the years after 2012. Columns 1 and 3 include only county and year fixed effects. Columns 2 and 4 include all county i's controls in year $t-1$. Panel B shows the regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area, when counties are split into two subsamples based on their political partisanship in the years before 2012. Columns 1 and 2 refer to the *Democratic* counties. Columns 3 and 4 refer to the *Republican* counties. The dependent variable is $\Delta\overline{EnvSust}_{i,t}$, i.e., county i's corporate environmental sustainability change in year t. The independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. Columns 1 and 3 include only county and year fixed effects. Columns 2 and 4 include all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)	(4)
Panel A (Balance test): Regressions of counties' fraction of wildfire burned area on the Democratic indicator variable				
	Before 2012		After 2012	
Democratic	-0.280	-0.278	0.040**	0.057**
	(0.177)	(0.206)	(0.018)	(0.029)
Controls	NO	YES	NO	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	453	453	390	390
Number of years	9	9	5	5
	0.363	0.364	0.287	0.290
Panel B: Regressions of counties' corporate environmental sustainability change on the fraction of their wildfire burned area in subsamples based on their political partisanship in the years before 2012				
	Democratic		*Republican*	
BurnedFrac	1.331**	1.285***	0.093	0.100
	(0.427)	(0.495)	(0.170)	(0.178)
Controls	NO	YES	NO	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	228	228	225	225
Number of years	9	9	9	9
R^2	0.581	0.596	0.360	0.406

Online Appendix Table 13

Regressions of counties' past and future change in the number of (i) air formal enforcement actions, (ii) air penalties, (iii) air informal enforcement actions, and (iv) air stack tests from the EPA on the fraction of their wildfire burned area

This table presents the regressions of counties' past and future change in the number (i) air formal enforcement actions, (ii) air penalties, (iii) air informal enforcement actions, and (iv) air stack tests from the EPA on the fraction of their wildfire burned area. Panel A refers county i's one- and two-year lagged and forward change in the number of air formal enforcement actions (i.e., the dependent variable is $\Delta FormActions_{i,t-1}$ in Column 1, $\Delta FormActions_{i,t-2}$ in Column 2, $\Delta FormActions_{i,t+1}$ in Column 3, and $\Delta FormActions_{i,t+2}$ in Column 4). Panel B refers to county i's one- and two-year lagged and forward change in the number of air penalties (i.e., the dependent variable is $\Delta Penalties_{i,t-1}$ in Column 1, $\Delta Penalties_{i,t-2}$ in Column 2, $\Delta Penalties_{i,t+1}$ in Column 3, and $\Delta Penalties_{i,t+2}$ in Column 4). Panel C refers to county i' one- and two-year lagged and forward change in the number of air informal enforcement actions (i.e., the dependent variable is $\Delta InformActions_{i,t-1}$ in Column 1, $\Delta InformActions_{i,t-2}$ in Column 2, $\Delta InformActions_{i,t+1}$ in Column 3, and $\Delta InformActions_{i,t+2}$ in Column 4). Panel D refers to county i' one- and two-year lagged and forward change in the number of air stack tests (i.e., the dependent variable is $\Delta StackTests_{i,t-1}$ in Column 1, $\Delta StackTests_{i,t-2}$ in Column 2, $\Delta StackTests_{i,t+1}$ in Column 3, and $\Delta StackTests_{i,t+2}$ in Column 4). In all panels, the independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. The list of controls includes county and year fixed effects and all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)	(4)
	1-year lagged	2-year lagged	1-year forward	2-year forward
Panel A: Regressions of counties' past & future change in the number of air formal enforcement actions				
$BurnedFrac$	-0.373	0.352	0.078	-0.124
	(1.055)	(0.326)	(1.252)	(1.064)
R^2	0.079	0.080	0.073	0.064
Panel B: Regressions of counties' past & future change in the number of air penalties				
$BurnedFrac$	-0.397	0.151	-0.655	-0.358
	(1.146)	(0.403)	(1.046)	(0.533)
R^2	0.078	0.072	0.082	0.068
Panel C: Regressions of counties' past & future change in the number of air informal enforcement actions				
$BurnedFrac$	-2.527	2.730	-0.394	-1.592
	(3.824)	(2.425)	(2.061)	(2.238)
R^2	0.074	0.072	0.089	0.097
Panel D: Regressions of counties' past & future change in the number of air stack tests				
$BurnedFrac$	7.940	6.137	8.047	1.236
	(9.369)	(6.585)	(7.441)	(1.653)
R^2	0.084	0.093	0.093	0.068
For all panels				
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	430	430	430	430
Number of years	13	12	13	12

Online Appendix Table 14

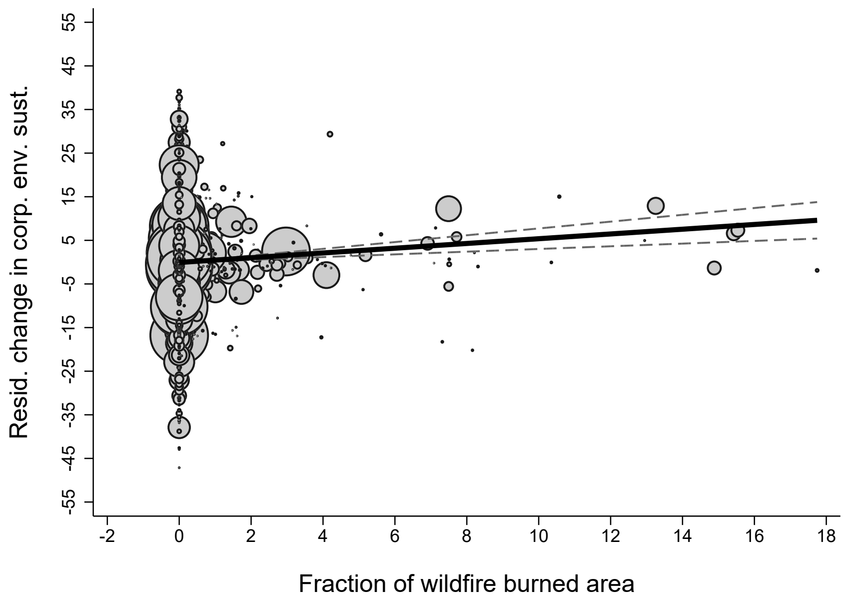
Subsample analysis of the local changes in the EPA enforcement actions

This table presents the regressions of counties' change in the number of (i) air formal enforcement actions, (ii) air penalties, (iii) air informal enforcement actions, and (iv) air stack tests from the EPA on the fraction of their wildfire burned area in subsamples based on their climate change opinion or political partisanship. In Panel A, the dependent variable is $\Delta FormActions_{i,t}$, i.e., county i's change in the number of air formal enforcement actions in year t. In Panel B, the dependent variable is $\Delta Penalties_{i,t}$, i.e., county i's change in the number of air penalties in year t. In Panel C, the dependent variable is $\Delta InformActions_{i,t}$, i.e., county i's change in the number of air informal enforcement actions in year t. In Panel D, the dependent variable is $\Delta StackTests_{i,t}$, i.e., county i's change in the number of air stack tests in year t. In all panels, the independent variable is $BurnedFrac_{i,t-1}$, i.e., county i's fraction of area burned by wildfires in year $t-1$. In Columns 1 and 2, counties are split into two subsamples based on the percent of households that believes in anthropogenic climate change. Column 1 refers to the $Believers$, i.e., counties where the percent of households that believes in anthropogenic climate change is above the median. Column 2 refers to the $Deniers$, i.e., counties where the percent of households that believes in anthropogenic climate change is below the median. In Columns 3 and 4, counties are split into two subsamples based on their political partisanship. Column 1 refers to the *Democratic* counties, i.e., counties where the majority of voters were Democrats in the most recent presidential election. Column 2 refers to the *Republican* counties, i.e., counties where the majority of voters were Republicans in the most recent presidential election. All columns control for county fixed effects and year fixed effects and all county i's controls in year $t-1$. The regressions are weighted by the total size of county i's firms (measured by their book value) in year $t-1$. The table depicts the coefficient estimates and the two-way clustered standard errors at the county and year level (in parenthesis). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. See Table 1 for sample characteristics and variable definitions.

	(1)	(2)	(3)	(4)
	Climate change opinion		Political partisanship	
	Believers	Deniers	Democratic	Republican
Panel A: Subsample regressions of counties' change in the number of air formal enforcement actions				
$BurnedFrac$	-0.761***	0.425*	-0.775***	1.195
	(0.205)	(0.231)	(0.216)	(0.817)
R^2	0.069	0.069	0.069	0.064
Panel B: Subsample regressions of counties' change in the number of air penalties				
$BurnedFrac$	-1.571**	0.400	-1.590**	1.125
	(0.768)	(0.309)	(0.769)	(0.792)
R^2	0.080	0.070	0.081	0.073
Panel C: Subsample regressions of counties' change in the number of air informal enforcement actions				
$BurnedFrac$	-1.988**	0.506	-2.019*	0.458
	(0.971)	(0.615)	(1.056)	(0.851)
R^2	0.090	0.114	0.092	0.121
Panel D: Subsample regressions of counties' change in the number of air stack tests				
$BurnedFrac$	8.632	5.375	8.701	-0.525
	(7.075)	(5.226)	(7.154)	(1.531)
R^2	0.110	0.083	0.112	0.100
For all panels				
Controls	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Average number of counties	215	215	211	219
Number of years	14	14	14	14

Online Appendix Fig. 1. Scatter plots of counties' residualized corporate environmental sustainability change on the fraction of their wildfire burned area for alternative measures of firms' size. The residuals are obtained from regressions that include county and year fixed effects, and are weighted by the total size of county i's firms in year $t-1$. In Appendix Subfigure 1a, the size of firms is measured by their market capitalization. In Appendix Subfigure 1b, the size of firms is measured by their total assets. Solid lines depict the linear fit prediction plots. Dashed lines depict the corresponding 95% confidence intervals.

(a) Firms' size measured by their market capitalization



(b) Firms' size measured by their total assets