CLIMATE CHANGE, AIR POLLUTION, AND CORPORATE PERFORMANCE: EVIDENCE FROM WILDFIRE SMOKE

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ABSTRACT

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This paper examines the effect of climate change on corporate performance. Using exposure to wildfire smoke as a novel setting, I document a significant physical effect of climate change on corporate operating income. On average, a one-standard-deviation increase of wildfire smoke exposure is associated with an $18.7 million loss in operating income. The effect is strongest for firms with high R&D-to-employee ratios, with high average labor costs, or that operate in industries that are highly dependent on skilled labor, suggesting that decreased productivity among high-skilled employees drives the observed effect. I also find that the stock market does not fully incorporate the effect of wildfire smoke into stock prices until annual earnings announcements. More climate change disclosure moderates the negative market reaction around annual earnings announcements. Overall, this paper documents the less salient effects of climate change on corporate performance and asset prices.

To Harlow and Sugar, for being the light of my life.
And to my parents, for allowing me to not work until 32.

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CHAPTER 1: INTRODUCTION

This paper examines the physical effects of climate change on the performance of US companies. Climate science establishes a strong relationship between rising temperatures and recent increases in other extreme weather events, including wildfires, hurricanes, and floods (Abatzoglou and Williams, 2016; United Nations, 2020). The US Environmental Protection Agency (EPA) estimates that natural disasters caused by climate change will cost the US alone at least $224 billion per year by 2090 (Martinich and Crimmins, 2019). The far-reaching effects of climate change on the global economy and ecology make climate change one of the biggest threats to humanity today (United Nations, 2021).

Investors and managers face three types of risk from climate change: the risk of physical damage, regulatory risk (e.g., the Cap-and-Trade Program and other greenhouse gas regulation), and technological risk (e.g., changes in demand caused by disruptive green technology, such as the electric vehicle). Institutional investors are the least concerned with the first category of risk--the physical effects of climate change (Krueger, Sautner, and Starks, 2020). This perspective is supported by extant research, which finds only limited evidence that climate change affects corporate performance in the US. For instance, Addoum, Ng, and Ortiz-Bobea (2020) find no evidence that extreme temperature shocks affect US establishment-level sales or employee productivity, suggesting that firms in developed countries may be resilient to climate change. Huynh and Xia (2021) find that while stock returns decline significantly for firms exposed to natural disasters, the returns bounce back in the following month, suggesting natural disasters have no significant impairment on long-term corporate performance. These studies focus on the immediate (*direct*) effects of climate change on firm operations and ignore the potential diffuse (*indirect*) effects. While the immediate effects of climate change are highly salient, they are relatively manageable because they are localized and predictable. For example, Entergy Corporation, a utility company based in New Orleans, relocated important business centers to Little Rock, Arkansas, and its transmission center to Jackson, Mississippi after Hurricane Katrina revised its assessments of climate risk (Sussman and Freed, 2008). Firms reliant on agricultural products, such as Anheuser-Busch InBev, have begun investing in research aimed at improving drought tolerance in key crops (CDP, 2020).

Firms are less able to predict and manage their exposure to the diffuse effects of distant climate disasters. Smoke from California wildfires travels as far as the East Coast, triggering air quality alerts in New York State (Gard and Garrett, 2021). Floods pollute drinking water for weeks, affecting public health in non-flooded regions long after the waters have receded (Hrdinka et al., 2012; Miller and Hutchins, 2017). These diffuse effects of climate change receive less attention despite their broad geographic and temporal reach and significant economic implications. Firms, investors, and research that focus only on the immediate effects of climate change may underestimate the true physical risk of climate change. The resulting underinvestment in climate change mitigation and suboptimal demand for climate change disclosure threaten the capital and goods market.[1]

This paper utilizes wildfire smoke to document the diffuse physical effects of climate change on corporate performance and market prices. Climate change has increased the incidence and doubled area lost to wildfires since the 1980s (Abatzoglou and Williams, 2016). While the most visible harms from wildfires and other climate disasters are immediate and localized, the diffuse effects of wildfires are far-reaching and, therefore, hard to predict. Smoke significantly increases

[1] In a recent survey by Deloitte, a-third of the companies are not taking any action to manage, mitigate or adapt to climate change because there is no significant pressure from shareholders or customers (Coppola, Krich and Blohmke, 2019).

the concentration of particulate matter many miles away from the originating wildfire, even when smoke is invisible to the human eye (Borgschult, Molitor, and Zou, 2020). While the West Coast is more prone to wildfires, wildfire smoke causes more deaths in the more heavily populated East Coast (O'Dell et al, 2021). On average, public firms in the US experience less than one day of significant wildfire risk (Griffin et al., 2020) but roughly 20 days of wildfire smoke exposure each year. Wildfire smoke, although less acute than the fire itself, affects many more firms.

Smoke exposure may disrupt firm-level operations by impairing employee productivity. Fine particulate matter ($PM_{2.5}$), one of six major air pollutants in wildfire smoke is a known health hazard. With a diameter of less than 2.5 micrometers, outdoor $PM_{2.5}$ can easily enter indoor spaces, irritating the nose, throat, and lungs; increasing the incidence of headaches and leading to heart disease (Pope, 2000; Sorenson et al., 2003). Extant research documents that high levels of $PM_{2.5}$ also reduce employee productivity and cognitive performance (Chang et al., 2016; Chen et al., 2017; La Nauze and Severnini, 2021). However, whether these effects are observable at the firm level is unclear.

In thick labor markets, employees especially susceptible to wildfire smoke may be temporally replaced. Tasks that do not require specialized skills or equipment may be quickly shifted to production centers with better air quality. However, firms that invest heavily in human capital have fewer effective smoke mitigation strategies available. Investment in human capital is concentrated in knowledgeable and high-skilled employees, who are both critical to operations and difficult to replace (Barney, 1991; Peteraf, 1993). For instance, an unproductive research and development (R&D) team member may delay the launch of a new drug while an unproductive production-line worker may not observably affect factory output. In the case of persistent smoke coverage or long-lasting health effects, chronically unproductive workers may be more easily replaced on the production line than on the R&D team (Farber and Hallock 2009; Blatter, Muehlemann, and Schenker 2012). Wildfire smoke exposure is, therefore, likely to influence firm performance most when it affects high-skilled and difficult-to-replace employees.

My analysis relies on the National Oceanic and Atmospheric Administration's Hazard Mapping System (HMS). The HMS uses high-resolution satellite images to track daily wildfire smoke coverage in the contiguous United States. Because wildfire smoke plumes can travel thousands of miles, this data allows me to disentangle the effect of smoke exposure from the immediate economic losses from wildfire damage. I aggregate daily smoke exposure data at the annual level to estimate the medium and long-run effects of wildfire smoke exposure in the county a firm headquarters.

On average, smoke exposure significantly reduces operating performance. A one-day increase in annual smoke exposure decreases return on asset (ROA) by 2.0 basis points, which corresponds to an average of $18.7 million loss in operating income for a 16-day (one standard deviation) increase in annual smoke exposure.[2] This estimation assumes that operations are concentrated near a firm's headquarters. Using headquarters smoke coverage may lead to measurement errors for firms with geographically dispersed operations. When excluding geographically dispersed industries, I find a stronger relationship between headquarters smoke exposure and firm performance.[3]

I conduct several cross-sectional tests to identify the mechanisms through which wildfire smoke exposure impairs firm performance. While exposure to wildfire smoke lower employee

[2] This magnitude is calculated based on the average book value of assets in a sample of US public firms. Effect on income = -0.0002*16 days*$5,842 million in assets = -$18.7 million. This magnitude is much larger than previous studies. For example, Pankratz, Bauer and Derwall (2021) find that a one standard deviation increase in the number of hot days leads to $1.8 million losses in non-US firms.

[3] In the robustness test, I rely on LexisNexis Corporate Affiliation Database to identify firm-level dispersed operations. Compared with including dispersed employees, I find a larger magnitude of smoke exposure after excluding firms with dispersed employees.

productivity uniformly, high-skilled employees are of greater importance to firm performance. Hence, the effect should be stronger when firm performance depends more on highly paid and skilled employees. Consistent with this hypothesis, cross-sectional tests show that wildfire smoke has a stronger effect on ROA among firms with higher R&D-to-employee ratios and higher average labor costs. In the third cross-sectional test, I examine the effect of wildfire smoke on firms with different employee replacement costs. I follow Ghaly, Dang, and Stathopoulos (2017) in constructing an industrial-level labor skills index. Industries that rely on highly skilled employees incur high costs to replace current employees because labor supply is limited (Farber and Hallock 2009; Blatter et al., 2012). I find that the effect of wildfire smoke on firm performance is stronger for firms in industries that rely on highly skilled employees.

I then examine whether capital market participants incorporate the effect of wildfire smoke exposure into security prices. Market participants may either directly price in wildfire smoke exposure or the resulting lower employee productivity. I find that increases in smoke exposure are associated with more negative earnings surprises, indicating financial analysts cannot accurately model the effect of wildfire smoke exposure on firm performance. Moreover, high smoke exposure is associated with a negative market reaction to annual earnings announcements.[4] Together, these findings suggest that the capital market does not yet fully incorporate wildfire smoke exposure into security prices.

The significant effects of wildfire smoke exposure on operating income and market reactions around earnings announcements prompt calls for additional climate change disclosure. However, it is unclear to what extent climate change disclosure will improve market efficiency. To shed light

[4] In a supplement test, I assign firms into four quartiles based on smoke exposure as of the year t-1. A trading strategy of buying and holding firms in the lowest smoke exposure quartile and selling firms in the highest smoke exposure quartile in year t can earn up 6.6% abnormal annual returns. The results are presented in Table A.1.

on this question, I explore whether voluntary disclosure of climate change exposure mitigates the effect of wildfire smoke on firm performance and the capital market. The benefits of disclosure are twofold: first, an improved information environment (Dhaliwal et al., 2011), and incentives for managers to investigate and proactively mitigate their climate change exposure (Downar et al., 2021). I use the proportion of climate-related keywords in the earnings conference call as a proxy for climate change disclosure (Sautner et al., 2020). I find that climate-change disclosure does not change the association between smoke exposure and ROA. However, high climate change disclosure mediates the negative association between smoke exposures and market reactions around earnings announcements. This result suggests firms with high climate change disclosures provide a better information environment to investors, which alleviates the underpricing of climate change risk.

This paper contributes to the accounting and finance literature on climate change by documenting that the significant effect of physical climate change on US firms is significant. Prior evidence that climate change affects corporate performance is concentrated in developing countries (Hsiang and Jina, 2014) but is limited for US firms (Addoum et al., 2020; Pankratz et al., 2021). This paper finds that the diffuse effects of climate change can significantly impair firm performance in the US.

A handful of studies find that sustained climate change reduces consumer demand and disrupts supply chains (Pankratz and Shiller, 2020; Jin et al., 2021), but a direct relationship between reductions in labor productivity following climate events and firm performance is limited. Pankratz et al. (2021) find that firms compensate for temporary reductions in labor productivity following climate disasters by increasing labor hours in subsequent quarters. My paper suggests that firms do not fully recover from the effect of wildfire smoke exposure on labor productivity, at least not in the short term.

This paper also contributes to the literature on the economic and health consequences of air pollution. This broad literature has documented evidence of air pollution's deleterious effects on health and labor productivity (e.g., Currie and Neidell 2005; Graff-Zivin and Neidell, 2012; Deryugina et al., 2019). Although this research establishes that air pollution impairs employee productivity, it does not necessarily lead to lower firm performance. A key challenge for measuring air pollution's causal effect on firm performance is in part driven by economic activities. Observed associations between air pollution and firm performance may be positive because pollutants are byproducts of operations. Using wildfire smoke as an exogenous source of air pollution, I document the effect of air pollution on firm performance.

Recent wildfires have captured the attention of researchers from multiple disciplines. Current studies document significant economic losses from fire damage and the health effects of wildfire smoke (Wettstein et al., 2018; Wang et al., 2021). Griffin et al. (2021) find that a firm is more likely to mention wildfire-related information when its headquarters county is at risk of exposure to wildfires. While some firms flag wildfires as a threat to firm operations, few reference wildfire smoke, which causes more persistent, unpredictable, and widespread disruptions.[5] I extend this literature by considering wildfire smoke, an overlooked, real effect of wildfires, on firm performance.

Finally, this paper examines the role of climate change disclosure in reducing investors' exposure to the effects of climate change. The capital market's failure to fully price the effects of climate change has policy implications regarding disclosure requirements. Although existing

[5] For example, Marriot mentions "wildfires" as a potential operational risk in the 2020 10-K.

literature finds that investors price in climate regulatory risk (Seltzer et al., 2020; Bolton and Kacperczyk, 2021; Ilhan, Sautner, and Vilkov, 2021), my findings suggest that investors most likely underestimate the physical threats of climate change. When climate disclosure is poor, the average $18.7 million loss in operating income from one standard deviation increase in smoke exposure is not reflected in capital market pricing before earnings announcements. I find that climate change disclosure improves the information environment and the capital market's ability to assess climate change risk.

CHAPTER 2: LITERATURE REVIEW

2.1. Literature on Climate Change

The extant economics literature on climate change focuses on the effect of extreme temperatures. Studies find that extreme temperatures have negative effects on labor supply and economic output. In particular, abnormal temperature shocks decrease gross domestic product (GDP) growth and exports in developing counties (Jones and Olken, 2010; Dell, Jones, and Olken, 2012). Abnormal temperatures also affect the US economy in specific industries. For example, Fisher et al. (2012) find that climate change reduces US agricultural yields. Graff-Zivin and Neidell (2014) examine the effects of temperatures on workers' time allocation in the US. They find that in industries with high exposure to weather conditions, employees reduce working hours when temperatures increase.

However, whether these changes in employee-level productivity have observable aggregate effects on firm performance is unclear. Using US establishment-level data, Addoum et al. (2020) find no evidence that temperature shocks affect sales or profit. Their study suggests a tenuous relationship between climate change and firm performance in developed counties. Huynh and Xia (2021) find that although the capital market has a significant negative reaction to climate disasters, prices bounce back in the following month. Their findings suggest that investors overreact to disasters. Using a sample of non-US firms, Pankratz et al. (2021) find extreme temperatures reduce firms' operating income because firms increase labor inputs to compensate for decreased productivity. The literature does not explore whether these results translate to the most developed US economy.

2.2. Wildfires and Air Pollution

Climate change is observable in changing weather patterns and the increased incidence of extreme weather events (National Park Service, 2018; National Interagency Coordination Center, 2020). The resulting high temperatures and low precipitation have contributed to the recent increase in wildfires. These changes have led to a 55% increase in the aridity of high-risk fire zones since the 1970s and doubled the annual acreage lost to wildfires since 1984 (Abatzoglou and Williams, 2016). While wildfire damage is localized, wildfire smoke plumes travel hundreds of miles downwind. Wildfire smoke contains a mixture of pollutants, including sulfur dioxide (SO_2), hazardous air pollutants (HAPs), and particle pollution. Fine particulate matter ($PM_{2.5}$) is the main component of wildfire smoke and is a known health hazard (EPA, 2021). Borgschulte et al. (2020) find a significant association between smoke exposure and same-day air pollution levels. Extensive medical literature finds a positive association between wildfire smoke and cardiovascular and respiratory illnesses (e.g., Wettstein et al., 2018).

Environmental economics shows that $PM_{2.5}$ and other air pollutants negatively affect labor outcomes. Hanna and Oliva (2015) find that an increase in air pollution, measured by levels of SO_2, leads to decreased working hours. Using a sample of wealthy households, Aragon, Miranda, and Oliva (2017) find that the negative association between air pollution and working hours is due to increased demand for childcare and eldercare. Chang et al. (2016) and Graff-Zivin and Neidell (2012) find that high levels of $PM_{2.5}$ have a sizable effect on short-term labor productivity for agricultural workers.

$PM_{2.5}$ can enter indoor spaces through closed windows and doors, affecting office worker productivity. Chang et al. (2019) find that call center workers have lower daily output when daily $PM_{2.5}$ levels are high. High levels of $PM_{2.5}$ impair both physical and cognitive performance, evidenced by test scores (Lavy, Ebenstein, and Roth, 2014) and reduced audit quality (Chen et al., 2017). La Nauze and Severnini (2021) further identify that the adverse effects of $PM_{2.5}$ on cognition are greatest for employees under fifty and workers engaged in problem-solving tasks.

While air pollution has clear adverse effects on individuals, its effect on firm performance is less straightforward because pollutants are byproducts of normal operations. Firms that pursue profit maximization tend to pollute more, and their abatement efforts largely depend on regulatory costs (Fowlie, 2010). As a result, observed associations between air pollution and firm performance may be positive. Using satellite data, Zou (2021) finds that cities with intermittent air monitoring experience significantly higher air pollution levels on unmonitored days, suggesting firms tend to increase pollution levels when the regulatory cost is low. Wildfire smoke introduces an exogenous source of air pollution that is not associated with economic activities or driven by local regulation, allowing me to examine the causal relationship between air pollution and firm performance.

CHAPTER 3: DATA AND SAMPLE

3.1. Wildfire Smoke Data

I obtain wildfire smoke data from National Oceanic and Atmospheric Administration's Hazard Mapping System (HMS). The HMS uses high-resolution satellite imagery from Geostationary Operational Environmental Satellite. Trained analysts process the satellite data to estimate smoke plumes over the contiguous United States each day. Although HMS data do not contain smoke height and intensity, the data's measure of smoke plume distribution is commonly used to capture daily smoke coverage (Aguilera et al., 2021).[6]

Following Miller et al. (2017) and Borgschulte et al. (2020), I use the HMS smoke plume data from 2006 to 2019 to construct daily smoke exposure at the county level.[7] I compare the HMS spatial data with county spatial data from the Census to determine if smoke plumes fully cover a county on a given day. I sum up smoke exposure days on an annual basis to construct a county-level smoke exposure measure.

3.2. Wildfire and Weather Data

To separate smoke exposure from actual wildfire risk, I collect wildfire records from the National Fire and Aviation Management group of the US Forest Service. This dataset consolidates wildfire records from the reporting systems of federal, state, and local fire organizations between 1992 and 2015 (Short, 2017). For the remaining years during the sample period, I collect the wildfire records from Monitoring Trends in Burn Severity (MTBS) and Wildfire Fire Decision Support System (WFDSS).

I further control for weather characteristics that could correlate with both wildfire smoke and firm performance. Temperature and precipitation data come from the PRISM Climate Group, the

[6] HMS analysts use fire detection algorithms to differentiate wildfire smoke from clouds or normal air pollution.
[7] The HMS data is available from September 2005.

US Department of Agriculture's official climatological database. This database provides daily temperatures and precipitation data in the contiguous US across 4 by 4 km grids. I use the weather observations closest to each county's centroid to construct weather conditions at the county level.

I obtain wind speed and wind direction data from the North American Regional Reanalysis (NARR) daily reanalysis data. This database provides daily wind conditions from land-based weather stations. Daily wind conditions consist of vector pairs, one for the east-west wind direction (u-component) and one for the north-south wind direction (v-component). Following prior literature (e.g., Deryugina et al., 2019), I calculate wind speed as $\sqrt{u^2 + v^2}$, where u and v are the county-day-level vectors. The wind direction is calculated as follows:

$$WINDDIR = \begin{cases} 270 - \theta \; if \; u > 0 \; and \; v > 0 \\ 270 + \theta \; if \; u > 0 \; and \; v < 0 \\ 90 + \theta \; if \; u < 0 \; and \; v > 0 \\ 90 - \theta \; if \; u < 0 \; and \; v < 0 \end{cases}$$

Where $\theta = \frac{180}{\pi} Arctan(\frac{|v|}{|u|})$. $WINDDIR$ indicates the wind direction, with zero corresponding to wind blowing from the north and higher values corresponding to clockwise movement around the compass. I average the estimated monitor-day level wind direction and speed to at the county-year level.

3.3. Firm-Specific Data

Firm data comes from the 2006 - 2019 period in the CRSP-Compustat merged database. I drop firms not traded on the NYSE, AMEX, or NASDAQ and firms that operate in the highly regulated financial and utility industries. Next, I use the headquarters zip code to identify firms' headquarters county location. Table 1 presents detailed sample selection procedures. The resulting sample contains 3,978 firms and 32,193 firm-year observations. Stock return data are obtained from the

CRSP database; earnings announcement dates are from the IBES database; financial statement data are from the Compustat database.

I obtain firm-level voluntary climate change exposure disclosure data (*CC_expo*) from Sautner et al. (2020), who use a machine-learning algorithm to measure climate change disclosure from earnings conference calls. The algorithm first identifies climate change bigrams by comparing training libraries of climate-related texts and non-climate-related texts. Then, it counts the frequency of climate change-related bigrams in each conference call transcript, scaled by the total number of bigrams in that transcript.[8] The authors find a significant association between *CC_expo* and climate-related events, such as the Paris Agreement and the Doha Climate Change Conference. I use the annual-level *CC_expo* in my analysis to match with the measure of wildfire smoke.

In the main analysis, I assume most of the firm performance changes are due to smoke exposure in the county where a firm is headquartered.[9] Measurement errors arise if a firm has establishments in different counties. In robustness tests, I obtain affiliate locations from the LexisNexis Corporate Affiliations Database. I identify all affiliation locations, including plants, units, subsidiaries, and branches, located in different counties from headquarters. This database also provides the number of employees that work in each affiliate. I use the number of affiliation employees and the total number of corporate employees to estimate the magnitude of potential measurement errors.

[8] Top ten keywords by frequency are "renewable energy," "electric vehicle," "clean energy," "new energy," "wind power," "wind energy," "energy efficient," "climate change," "greenhouse gas," "solar energy."

[9] Henderson and Ono (2008) show that a firm's major plants and operations are typically located close to a firm's headquarters. Pirinsky and Wang (2006) note that corporate headquarters are usually close to core business activities.

Table 1 Sample Selection

This table presents the sample selection procedures in the main analysis sample. The sample period is from 2006 to 2019.

	Observations	**Firms**
Firm-year observations from 2006 through 2019 in Compustat	71,036	9,423
Less: firms not listed on Amex, NYSE, and NASDAQ	(8,517)	
Less: observations without location information	(15,535)	
Less: financial and utility firms	(13,793)	
Less: observations with less than 1 million assets	(101)	
Less: observations with insufficient data for control variables	(897)	
Main Sample	32,193	3,978

CHAPTER 4: RESEARCH DESIGN

Because wildfire smoke plumes travel thousands of miles, I can examine the effect of smoke exposure independent of the direct economic losses caused by wildfires using the following equation:

$$Performance_{it} = \beta \cdot SmokeDays_{ct} + Control\,Variables + \alpha_i + \alpha_t/\alpha_{st} + \varepsilon_{it} \quad (1)$$

The primary measure of firm performance is ROA, which equals operating income standardized by total assets in year t-1. Compared with net income, operating income is subject to less distortion from accounting choices (Moliterno and Wiersema, 2007).[10] The primary measure of smoke exposure is $SmokeDays_{ct}$, which equals the number of days a county is fully covered by wildfire smoke each year t. I use headquarters location to determine a firm's smoke exposure. In the robustness test, I replace $SmokeDays_{ct}$ with $SmokeIntensity_{ct}$, which equals the difference between air quality index (AQI) during smoke days and non-smoke days.

This estimating equation includes firm fixed effects (α_i) to isolate within-firm differences in the effect of smoke exposure. Including firm fixed effects also partially alleviate the concern that $SmokeDays_{ct}$ does not capture the intensity of smoke coverage. Year fixed effects (α_t) or industry by year fixed effects (α_{st}) account for correlations between smoke exposure and economic trends. I control for wildfire events-the number of days that a county experienced wildfires-to separate the effect of smoke exposure from wildfire damages. I also control for weather patterns that may directly affect financial performance (Addoum et al., 2020) and correlate with smoke exposure (Miller et al., 2017; Borgschult et al., 2020). The time-varying weather characteristics include annual counts of the number of days above 30°C and below 0°C, the annual precipitation level, and annual average wind conditions closest to each county's centroid.

[10] In the robustness test, I also examine the effect of smoke exposure on net profit standardized by total assets.

Following the literature on air pollution (e.g., Deryugina et al, 2019; Borgschult et al., 2020), I weight regressions by county population in each year so that my estimates reflect the experience of a representative employee.

CHAPTER 5: RESULTS

5.1. Descriptive Statistics

Table 2 provides summary statistics of the main analysis sample. A firm's exposure to wildfire smoke is not uncommon. On average, firms are fully covered by smoke plumes for days (14 weekdays) a year during the 2006-2019 sample period. Smoke exposure is closely related to wildfires. Around half of the observations located in counties experienced at least one wildfire throughout the year. Counties on average experience 30 days with some wildfire activities each year. However, the incidence of meaningful wildfire exposure is much lower-around one day per year (Griffin et al., 2021). An average firm experiences 8 days of average temperature above 30^{o}C and 22 days of average temperature below 0^{o}C each year. The average ROA is 8%, and the average 3-day cumulative abnormal return around earnings announcements is 0.38%.

Table 2 Summary Statistics

This table presents the summary statistics in the analysis sample. The sample period is 2006-2019. All firm-specific variables are winsorized at the 1st and 99th percentiles.

Variable Name	N	Mean	St Dev	P25	P50	P75
Dependent Variables						
Operating Income/Asset (%)	32,193	7.993	20.504	5.022	11.575	17.751
Operating Expense/Asset (%)	32,193	102.049	72.667	50.444	83.350	133.008
Sale/Asset (%)	32,193	109.318	76.795	55.180	91.441	143.835
CAR [-1, 1] (%)	22,652	3.822	8.038	2.281	4.611	6.649
Earning Surp (%)	24,008	0.351	8.598	-4.148	0.300	5.009
Net Income/Asset (%)	32,367	-0.964	20.423	-2.837	3.907	8.588
Weather/Economic Characteristics						
SmokeDays	32,193	20	16	8	16	28
WildFire	32,193	30	80	0	1	21
GDP Percap	32,193	10.944	0.341	10.704	10.901	11.106
County Population	32,193	1,602,642	1,803,899	597,597	991,847	1,765,137
Wind Direction	32,193	202.014	27.678	191.379	208.506	218.489
Wind Speed	32,193	3.351	0.867	2.747	3.216	3.5443
Temp above 30	32,193	7.709	14.704	0.000	4.000	9.000
Temp below 0	32,193	20.326	31.791	0.000	0.000	39.000
Precip (mm)	32,193	10.944	0.341	10.70385	10.901	11.106
Firm Characteristics						
Asset	32,193	5,842.484	2,7753.89	171.249	710.1	2,784.349
R&D	32,193	0.061	0.114	0.000	0.006	0.073
Leverage	32,193	0.198	0.208	0.002	0.151	0.314
Sales Growth	32,193	0.128	0.402	-0.024	0.065	0.180
M/B	32,193	2.364	2.055	1.188	1.703	2.685
PPE/Asset	32,193	0.257	0.257	0.072	0.162	0.355
Tobin's Q	32,193	2.078	1.463	1.184	1.597	2.388
R&D/Emp	17,361	0.075	0.143	0.006	0.022	0.064
Labor Cost	31,575	0.183	2.063	0.039	0.087	0.176
Labor Skills	28,205	2.618	0.529	2.249	2.583	2.998

Figure 1 provides summary statistics for the annual frequency and geographic distribution of smoke events in our sample. The Midwest states tend to have high smoke exposure, and the southwest states experience low smoke exposures. Smoke exposure also changes each year significantly, with a standard deviation of 16 days.[11]

[11] Perhaps counter-intuitively, the smoke coverage in California is lower than the country average. This is due to wind conditions and is consistent with the anecdotal evidence (Saldanha, 2021). California has significantly more days of smoke exposure in 2018, when it experienced the worse fires in history.

Figure 1 County Annual Wildfire Smoke Exposure

This figure plots the number of days a county is fully covered by wildfire smoke in selected years. The sample period is 2006-2019. Darker colors suggest more smoke days.

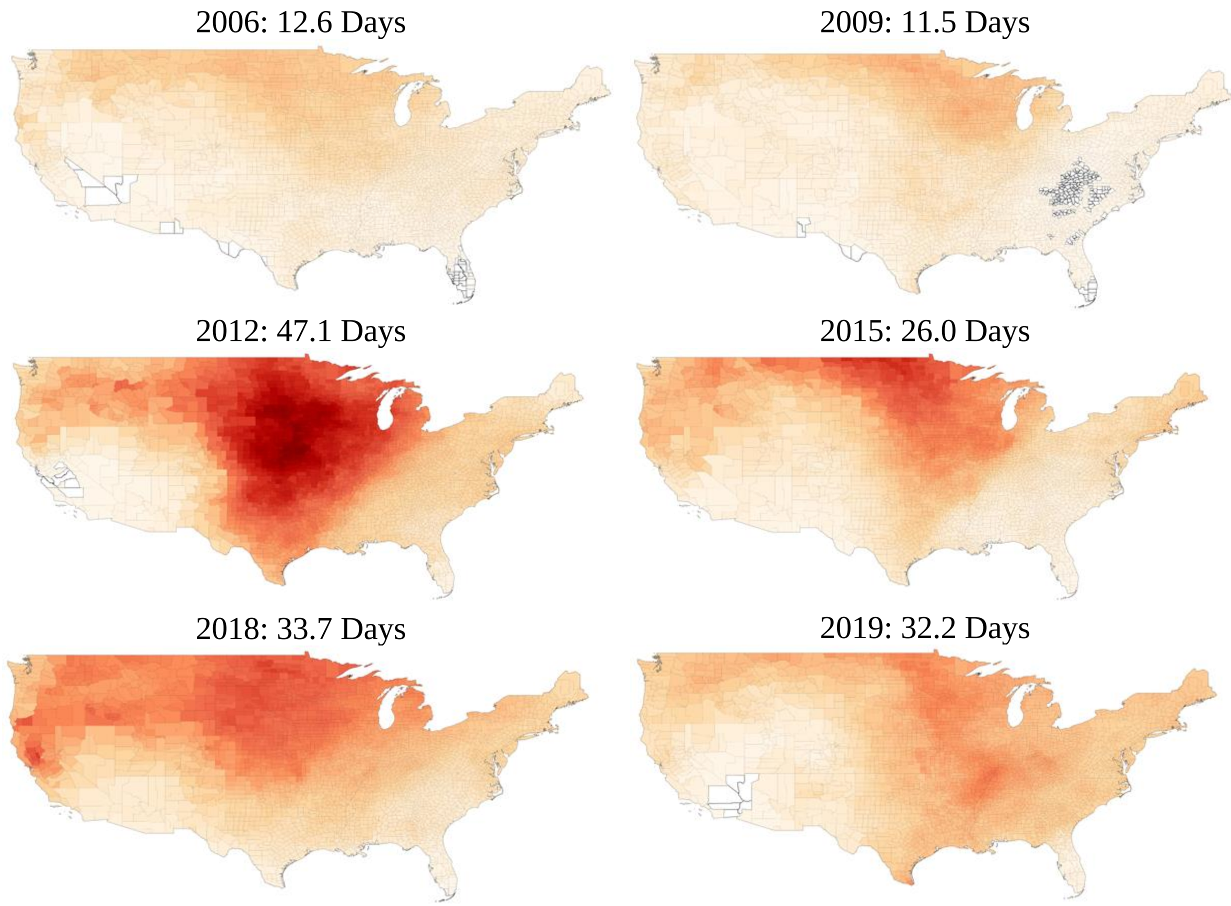


Figure 2 illustrates the wildfires and smoke in the contiguous US on April 10th, 2018. This plot shows that fire-related smoke can travel across the country. This feature allows us to separate the effect of wildfire smoke from direct fire damages. In figure 3, we present the coefficient of regressing air quality index (AQI) on indicators of daily smoke exposure [-10, 10] days around the day of smoke exposure. To alleviate the concern that smoke is correlated with same-county wildfires, we exclude daily observations if a county also experienced a wildfire. We find a significant arise of AQI around the smoke coverage date. Figure 4 plots the counties that are covered in the analysis sample. The sample contains 421 unique counties. Although the sample only represents a small fraction of counties, those counties are home to 68.7% of the US population, according to the 2010 Census.

Figure 2 Fire and Smoke on April 10th, 2018

This map plots the fire and smoke in selected US states on April 10th, 2018. The red triangles represent fire locations, and grey areas are smoke coverage.

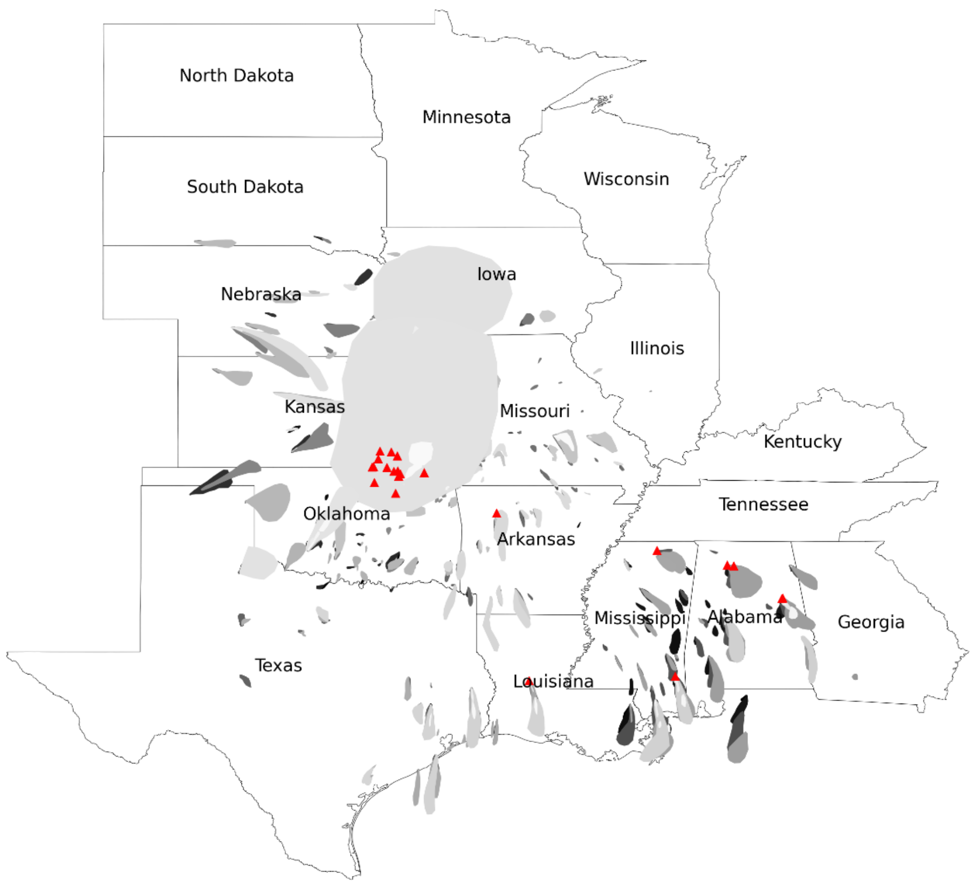


Figure 3 Wildfire smoke and Air Quality Index (AQI)

This figure plots the coefficients of regressing AQI on indicators of daily smoke exposure [-10, 10] days around the day of smoke exposure. The baseline AQI is 10 days before each smoke coverage date. We exclude daily observations if a county also experienced a wildfire. The regression includes county by year-month fixed effects. Standard errors are clustered at the state levels.

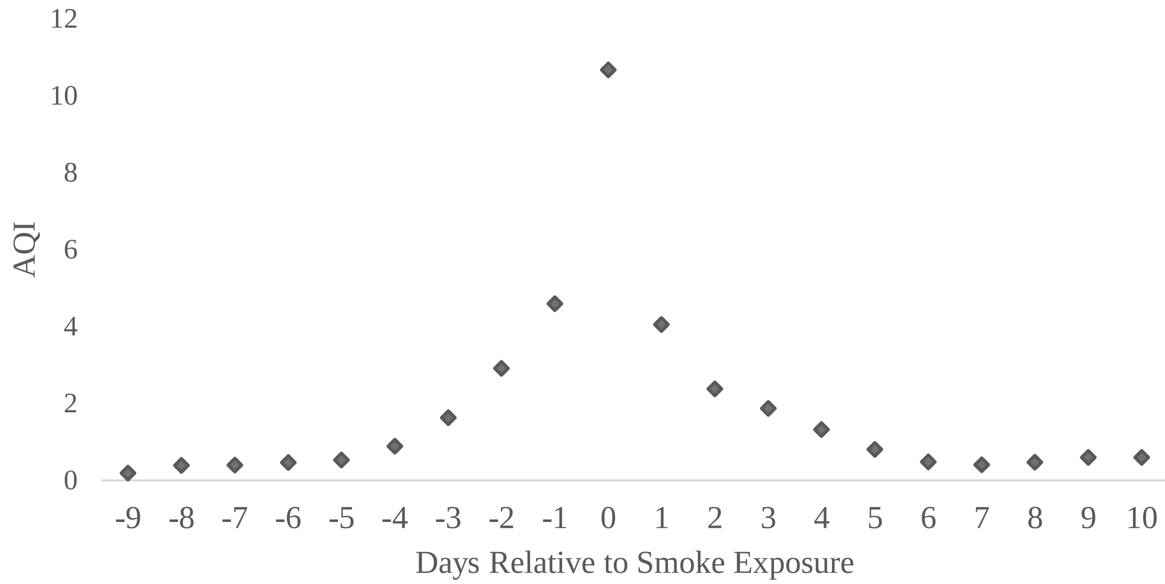
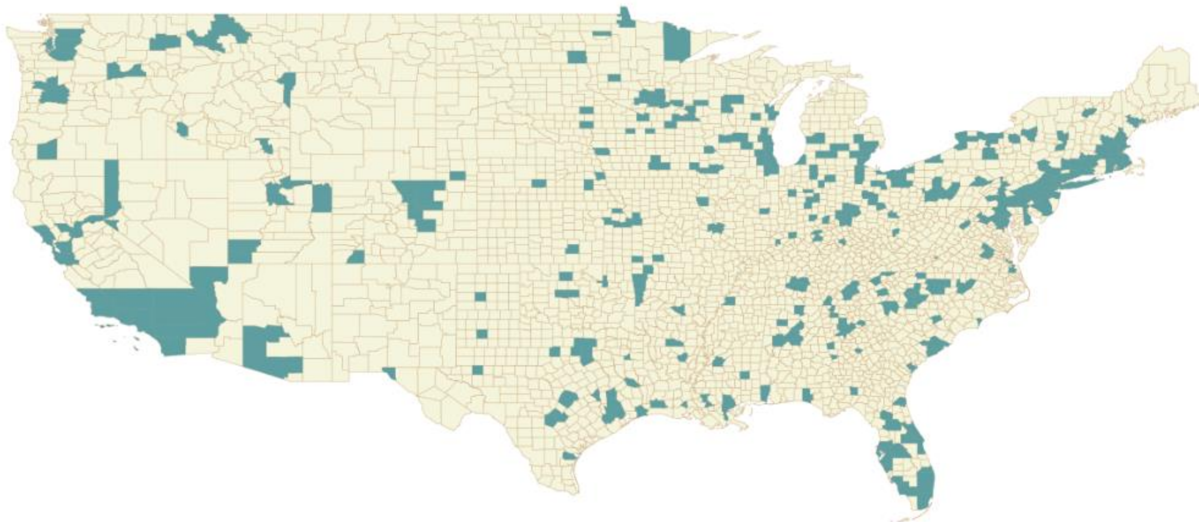


Figure 4 Firm Locations

This figure highlights the counties where sample firms' headquarters locate. The sample contains 421 counties, which cover 68.7% of the US population according to the 2010 Census.



5.2. Baseline Result

Table 3 presents the baseline effect of wildfire smoke on ROA. In column 1, I control for wildfire and weather characteristics. This column does not include further county-level GDP or firm-level control variables to avoid "over-controlling problems" in climate-economy literature (Dell, Johns, and Olken, 2014).[12] Column 2 adds controls for county-level GDP and firm characteristics. I find that more days of smoke exposure significantly reduce a firm's financial performance at the 95% confidence interval in both columns. The economic magnitude is non-trivial. According to the coefficient estimate in column 2, a one-day increase in annual smoke exposure decreases ROA by 2.0 basis points. A one standard deviation (16 days) increase in annual smoke exposure decreases ROA by 32 basis points, corresponding to an $18.7 million loss in operating income for an average firm (based on the book value of assets). Perhaps unsurprisingly, more days of wildfires are associated with lower ROA. In column 3, I replace year fixed effects with 3-digit SIC industry by year fixed effects to alleviate the concern that the county-level smoke exposure measure captures industry-level performance trend and industry agglomeration. The estimated coefficient on smoke exposure decreases slightly but is still statistically significant.

So far, I have assumed that most operating performance changes are due to smoke exposure in the county where a firm is headquartered. This assumption can lead to measurement errors if a firm has significant operations in other counties. Measurement errors in smoke exposure should result in an attenuation bias. To reduce potential measurement errors, column 4 excludes firms in industries known to have geographically dispersed workforces: retail, wholesale, and transportation industries. Compared with column 3, I find a slightly larger effect of smoke exposure on firm performances, suggesting that measurement errors bias against the estimation. In

[12] "Over-controlling problems" happen when control variables are also the consequences of climate change and will bias the estimation.

column 5, I exclude firms headquartered in California, a state known for its widespread wildfire risk. . I find the baseline result is robust to excluding California.[13]

One drawback of this measure is the lack of smoke intensity. For example, the state of California has fewer days of smoke exposure than the country average, but the smoke intensity should be much higher due to its wildfire activities. The inclusion of firm fixed effects partially alleviates the measurement error because the coefficient estimates capture within-firm year-over-year differences. In section 6.3, I further addressed this issue by utilizing the daily air quality index (AQI) from EPA as a proxy for smoke intensity.

[13] The results are also robust to excluding firms that headquartered in states with significant wildfires. Section 6.2 provides more deatailed discussions.

Table 3 Firm Performance Effects of Wildfire Smoke

This table presents the effect of wildfire smoke on firm performance. The dependent variable is operating income before depreciation divided by total assets in year t-1. The interested independent variable is SmokeDays, which equals the number of days the county where a firm headquartered are covered by wildfire smoke. Columns 1 and 2 include firm fixed effects and year fixed effects. Columns 3 and 4 include firm fixed effects and industry by year fixed effects, and Column 4 excludes firms operating in geographically dispersed industries. Column 5 excludes firms operating in California. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1)	(2)	(3)	(4)	(5)
	Operating Income/Asset (%)				
				Exclude Disperse Ind	*Exclude California*
SmokeDays	-0.0202**	-0.0202***	-0.0182***	-0.0201***	-0.0319***
	(0.0077)	(0.0045)	(0.0057)	(0.0066)	(0.0103)
WildFire	-0.0040***	-0.0036***	-0.0017***	-0.0025***	
	(0.0009)	(0.0008)	(0.0006)	(0.0007)	
Wind Speed	1.4826	0.9756	0.6620	0.8393	1.2726
	(0.9333)	(0.7883)	(0.5606)	(0.7630)	(1.0046)
Wind Direction	-0.0134	-0.0067	-0.0020	-0.0010	-0.0138
	(0.0110)	(0.0074)	(0.0094)	(0.0111)	(0.0123)
Temp above 30	0.0119	-0.0056	0.0113	0.0125	-0.0118
	(0.0243)	(0.0180)	(0.0114)	(0.0100)	(0.0180)
Temp below 0	0.0060	-0.0046	0.0040	0.0014	-0.0110
	(0.0194)	(0.0130)	(0.0087)	(0.0090)	(0.0161)
Precip	-0.0015**	-0.0006	0.0003	0.0005	-0.0012***
	(0.0006)	(0.0005)	(0.0005)	(0.0006)	(0.0004)
GDP Percap		10.9416*	7.9946*	8.3183*	12.1952***
		(5.4631)	(4.3658)	(4.7759)	(3.7332)
		(3.1962)	(3.4291)	(4.1115)	(3.1921)
Observations	32,386	31,743	31,017	26,242	26,847
Adjusted R-squared	0.7591	0.7978	0.8142	0.8125	0.7857
Fixed Effect	Firm, Year	Firm, Year	Firm, Ind by Year	Firm, Ind by Year	Firm, Year

5.3. Wildfire Smoke and Cross-sectional Tests

I hypothesize that wildfire smoke leads to lower firm performance through reducing labor productivity. While higher levels of $PM_{2.5}$ brought by wildfire smoke reduce productivity for both indoor and outdoor employees (Chang et al., 2016; 2019), high-skilled employees are of greater importance to firm performance because they are key components of a firm's competitive advantage (Barney, 1991; Lengnick-Hall, 1992; Peteraf, 1993; Crook et al., 2011). Furthermore, high-skilled employees are more costly to replace due to limited labor supply (Ghaly et al., 2017). If the effect of wildfire smoke on firm performance is through reducing labor productivity, firms that rely more on high-skilled employees and have less flexibility to adjust their labor demand should suffer higher losses from wildfire smoke.

5.3.1. Firm-level Differences

I conduct three cross-sectional tests to examine this hypothesis. High-skilled employees are of greater importance to firms with a higher emphasis on innovation (Zingales, 2000). In the first cross-sectional test, I follow the previous literature and use R&D investment per employee to proxy firms' emphasis on innovation (Hill and Snell, 1988; Kor, 2006). A small decrease in R&D employees' performance is likely to lead to a significant decrease in firm performance. Columns 1 and 2 of Table 4 present the estimation results. I restrict the sample to firms with positive R&D investment and further divide firms into two subsamples. The effect of wildfire smoke is much stronger in firms with higher R&D to employee ratios. In this subsample, one standard deviation (16 days) increase in annual smoke exposure decreases ROA by 58 basis points. Wildfire smoke has a smaller magnitude and insignificant effect on firms with lower reliance on human capital.[14]

[14] Following Bhojraj, Sengupta, and Zhang (2017), I use z-statistics to test equality of two coefficients. The formula is $\frac{\beta_1-\beta_2}{\sqrt{SE1^2+SE2^2}}$

In untabulated tests, I interact the R&D-to-employee ratio with wildfire smoke exposure. I find that the estimated coefficient on the interaction term is significantly negatively associated with ROA, suggesting that a firm is subject to higher impairment from wildfire smoke when its reliance on innovation increases. An alternative explanation for this cross-sectional test is that in firms with a high R&D-to-employee ratio, employees are more likely to work near headquarters. If so, firms in the subsample with high R&D-to-employee ratios may be subject to lower measurement errors in the wildfire smoke exposure variable. To rule out this alternative explanation, I focus on a two-digit SIC industry with the highest R&D to employee ratio in my sample (two-digit SIC = 28). I run model (1) with this subsample, and I find that the $SmokeDays \times R\&D/Emp$ interaction term is still significantly negative. Overall, these results suggest that even in the industry with the highest reliance on R&D, the effect of smoke exposure on firm performance is stronger when a firm's R&D-to-employee ratio is high.

Skilled labor, however, exists outside R&D teams. As skilled employees are likely to demand higher pay, I examine the heterogeneous effects of wildfire smoke among firms categorized by labor costs per employee. I use selling, general & administrative expense (SG&A) divided by the number of employees as a proxy for a firm's average labor costs. I expect that firms with high labor costs are likely to suffer more from wildfire smoke than those with low labor costs. Columns 3 and 4 of Table 4 present this cross-sectional test. The effect of wildfire smoke is concentrated among firms with higher average labor costs. In this subsample, one standard deviation (16 days) increase in annual smoke exposure decreases ROA by 40 basis points. On the other hand, firms with lower average labor costs have reductions in ROA from wildfire smoke exposure that are smaller magnitudes and statistically insignificant.

Table 4 Human Capital and Effects of Wildfire Smoke

This table presents the effect of wildfire smoke on firm performance with different levels of human capital importance. The dependent variable is operating income before depreciation divided by total assets in year t-1. The proxy for human capital importance is the R&D expenditure per employee, and the sample is restricted to firms with R&D expenditures. In columns 3-4, the proxy for human capital importance is labor cost. All columns include firm fixed effects and year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1)	(2)	(3)	(4)
	Operating Income/Asset (%)			
	Above-Median R&D/Emp	Below-Median R&D/Emp	Above-Median Labor Cost	Below-Median Labor Cost
SmokeDays	-0.0344***	-0.0020	-0.0252***	-0.0077
	(0.0124)	(0.0068)	(-0.0079)	(0.0065)
WildFire	-0.0335**	-0.0471***	-0.0057***	-0.0019*
	(0.0156)	(0.0129)	(0.0015)	(0.0010)
Wind Speed	1.0114	2.0473**	2.1196**	-0.3962
	(0.7654)	(0.8670)	(0.8982)	(0.7233)
Wind Direction	0.0644**	-0.0344*	0.0145	-0.0186
	(0.0251)	(0.0188)	(0.0151)	(0.0118)
Temp above 30	0.0295	-0.0180	-0.0026	-0.0136
	(0.0284)	(0.0207)	(0.0204)	(0.0150)
Temp below 0	0.0205	-0.0215	0.0012	-0.0101
	(0.0190)	(0.0141)	(0.0181)	(0.0081)
GDP Percap	0.9437	11.3316	8.8029	9.6897**
	(11.7091)	(6.8616)	(7.3151)	(4.4284)
Precip	0.0011	-0.0011***	-0.0012	-0.0001
	(0.0010)	(0.0004)	(0.0012)	(0.0003)
Z test of Difference between Coefficients	-2.2910**		-1.7106*	
Observations	8,831	8,690	15,681	15,314
Adjusted R-squared	0.8254	0.7543	0.8040	0.7174
Fixed Effect	Firm, Year	Firm, Year	Firm, Year	Firm, Year

5.3.2. Industry-level Differences

The previous two tests examine heterogeneity in the effect of wildfire smoke caused by firm-level characteristics. In the third cross-sectional test, I examine the effect of wildfire smoke on firm performance in industries with different levels of labor replacement costs. I follow Ghaly et al. (2017) in constructing industry reliance on skilled labor as $\sum_{j=1}^{O}(\frac{E_{ji}}{E_i} * Z_j)$, where Z_j is required occupation skill-level identified by O*NET. E_{ji} is the number of employees in four-digit NAICS industry i working in occupation j , E_i is the total number of employees in industry i, and O is the total number of occupations in industry i. Industries with higher dependence on skilled labor incur higher costs to replace current employees due to limited labor supply (Farber and Hallock 2009; Blatter, Muehlemann, and Schenker 2012). Therefore, if wildfire smoke affects firm performance by decreasing employee productivity, the observed effect should be stronger when a firm has higher labor replacement costs. In Table 5, I separate the sample into two subsamples based on a firm's labor replacement costs. Consistent with my hypothesis, I find the effect of wildfire smoke is concentrated among firms with high labor replacement costs. In this subsample, a one standard deviation (16-day) increase in annual smoke exposure decreases ROA by 52 basis points.

Table 5 Labor Skill and Effects of Wildfire Smoke

This table presents the effect of wildfire smoke on firm performance with different levels of labor skills. The dependent variable is operating income before depreciation divided by total assets in year t-1. The measure for labor skill follows Ghaly et al. (2017). Columns 1 includes the subsample with above-median labor skills, and columns 2 includes the sample with below-median labor skills. Both columns include firm fixed effects and year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1)	(2)
	Operating Income/Asset (%)	
	Above-Median Labor Skill	Below-Median Labor Skill
SmokeDays	-0.0307**	-0.0032
	(0.0132)	(0.0090)
WildFire	-0.0427***	-0.0053
	(0.0130)	(0.0104)
Wind Speed	1.3088**	-0.4717
	(0.6155)	(1.2779)
Wind Direction	0.0218	-0.0080
	(0.0200)	(0.0214)
Temp above 30	0.0079	-0.0167
	(0.0168)	(0.0197)
Temp below 0	-0.0146	-0.0017
	(0.0148)	(0.0128)
GDP Percap	15.9184**	6.7598
	(6.4737)	(4.7215)
Precip	-0.0016**	-0.0004
	(0.0006)	(0.0004)
Z test of Difference between Coefficients	1.7213*	
Observations	14,191	14,014
Adjusted R-squared	0.8198	0.7742
Fixed Effect	Firm, Year	Firm, Year

5.3.3. County-level Differences

According to Figure 1, the Midwest region is subject to more days of smoke coverage than the west coast and the east coast due to wind conditions. It is possible the the negative association between smoke coverage and firm performance is also concerntrated in the Midwest. To further disentangle the differential effect of smoke exposure, I examine the effect of smoke coverage on firm performance with respect to different levels of county-level economic characteristics: population and income per capita.

Table 6 presents the effect. I find that the effect of smoke coverage on operating income is statistically significant in counties with above-median population and income per capita, and statistically insignificant in counties with below-median population and income per capita. This result is consistent with Borgschulte et al (2021), who find that the adverse effect of air pollution on labor market is more severe in counties with above-median urbanization rate and home value. This finding also alleviates the concern that the negative association between smoke coverage and firm performance is a result of weaker economic conditions in the Midwest region.

Table 6 County Characteristics and Effects of Wildfire Smoke

This table presents the effect of wildfire smoke on firm performance in counties with different size of populations and income. The dependent variable is operating income before depreciation divided by total assets in year t-1. Columns 1 includes the subsample with above-median county population, and columns 2 includes the sample with below-median county population. Columns 3 includes the subsample with above-median income per capita, and columns 4 includes the sample with below-median income per capita. All columns include firm fixed effects and year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1)	(2)	(3)	(4)
	Operating Income/Asset (%)			
	Above-Median Population	Below-Median Population	Above-Median Income	Below-Median Income
SmokeDays	-0.0194***	-0.0045	-0.0113*	-0.0146
	(0.0059)	(0.0153)	(0.0059)	(0.0134)
WildFire	-0.0241*	-0.0047	0.0135	-0.0006
	(0.0127)	(0.0183)	(0.0119)	(0.0150)
Wind Speed	0.9939	1.1011	2.9895***	1.1560
	(1.0128)	(0.6704)	(0.6181)	(1.2492)
Wind Direction	-0.0011	-0.0023	-0.0443***	-0.0038
	(0.0093)	(0.0158)	(0.0162)	(0.0139)
Temp above 30	-0.0085	-0.0026	-0.0184	-0.0216
	(0.0213)	(0.0247)	(0.0376)	(0.0204)
Temp below 0	-0.0064	0.0035	0.0067	-0.0170
	(0.0147)	(0.0063)	(0.0059)	(0.0184)
GDP Percap	14.1577*	3.1432	5.6517***	7.5806
	(7.7532)	(2.4856)	(1.8741)	(6.7335)
Precip	-0.0008	0.0000	-0.0010	-0.0004
	(0.0006)	(0.0006)	(0.0007)	(0.0005)
Z test of Difference between Coefficients	0.9086		0.2254	
Observations	15,674	16,083	15,969	15,517
Adjusted R-squared	0.7955	0.8064	0.8374	0.7747
Fixed Effect	Firm, Year	Firm, Year	Firm, Year	Firm, Year

5.4. Effect of Wildfire Smoke on Sales and Productivity

Human capital is a key source of competitive advantage. A small percentage of input loss from idiosyncratic shocks can significantly decrease sales without lowering demand (Barrot and Sauvagnat, 2016). Using a sample of non-US firms, Pankratz et al. (2021) find that lower employee productivity from high temperatures leads to decreased sales revenue. If wildfire smoke leads to lower employee input, lower sale revenue should be an important portion of decreased operating income. Alternatively, firms may be able to compensate for reductions in employee productivity by increasing labor inputs. Such mitigation strategies would be observed as increases in total operating expense without significant changes to sales revenue.

Table 7 presents the effects of wildfire smoke on sales revenue and operating expense. I find that more days of smoke exposure lead to lower sales revenue instead of higher operating costs. Specifically, a one standard deviation (16-day) increase in annual smoke exposure decreases $Sales\ Revenue/Asset$ by 59 to 81 basis points, corresponding to a \$34 to \$47 million loss in sales revenue for a firm with an average book value of assets. Columns 3 and 4 of Table 6 show that operating expense decreases insignificantly, suggesting firms do not significantly increase labor input to compensate for the lost productivity in the short run.

Table 7 Impact of Wildfire Smoke on Sales and Expenses

This table presents the effect of wildfire smoke on sales and expenses. In columns 1-2, the dependent variable is Sale/Asset, which equals sales revenue divided by asset in year t-1. In columns 3-4, the dependent variable is operating expense, which equals total operating expense divided by asset in year t-1. The interested independent variable is SmokeDays, which equals the number of days the county where a firm headquartered are covered by wildfire smoke. Columns 1 and 3 include firm fixed effects and year fixed effects, columns 2 and 4 include firm fixed effects and industry by year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1)	(2)	(3)	(4)
	Sale/Asset (%)		Operating Expense/Asset (%)	
SmokeDays	-0.0369**	-0.0508**	-0.0173	-0.0288
	(0.0174)	(0.0224)	(0.0164)	(0.0205)
WildFire	-0.0100***	-0.0050	-0.0058***	-0.0026
	(0.0024)	(0.0043)	(0.0021)	(0.0041)
Wind Speed	0.4148	-2.3487*	-0.3935	-2.7164**
	(1.6733)	(1.2677)	(1.5440)	(1.2880)
Wind Direction	-0.0030	0.0450	0.0006	0.0482
	(0.0257)	(0.0286)	(0.0268)	(0.0299)
Temp above 30	-0.0293	0.0342	-0.0225	0.0277
	(0.0325)	(0.0323)	(0.0157)	(0.0292)
Temp below 0	0.0023	0.0058	0.0092	0.0014
	(0.0315)	(0.0359)	(0.0222)	(0.0305)
GDP Percap	26.4051**	15.8621***	11.7600**	6.7097
	(10.7259)	(5.6345)	(4.7625)	(4.6648)
Precip	-0.0002	0.0014	0.0007	0.0014
	(0.0013)	(0.0014)	(0.0006)	(0.0009)
Observations	31,755	31,026	31,755	31,026
Adjusted R-squared	0.8724	0.9015	0.8753	0.9015
Fixed Effect	Firm, Year	Firm, Ind by Year	Firm, Year	Firm, Ind by Year

5.5. Wildfire Smoke and Earnings Announcements Return

In this section, I examine whether smoke exposure predicts the unexpected component of firm performance. Despite significantly increasing particulate matter concentration, most wildfire smoke events can only be seen from satellites and are invisible to human eyes (Beitler, 2006; Borgschulte et al., 2020). The effect of smoke exposure on firm performance is less salient than the effect of wildfire damage and, therefore, may surprise market participants. Alternatively, if the market is efficient, market participants may incorporate publicly available wildfire smoke data into prices.

In Table 8, column 1 examines whether financial analysts have taken climate-related information into earnings forecasts. Following the literature on analyst forecast accuracy, I calculate the earnings surprise as the difference between actual earnings per share and average forecasted earnings per share divided by the month-end share price before the annual earnings announcement. I find that wildfire smoke exposure is associated with negative earnings surprises. This result suggests that although sell-side analysts integrate sustainability scores into stock recommendations (Eccles, Krzus, and Serafeim 2011), they may underestimate the threats of climate change on firm performance.

Analysts do not fully consider information on smoke exposure. A natural question is whether investors anticipate the effect of smoke exposure on firm performance. If the market fully understands the effect of smoke exposure on corporate performance, there should be little information content related to earnings around earnings announcements. In column 2 of Table 8, I examine the association between smoke exposure and [-1, 1] day cumulative abnormal returns (CAR) around the annual earnings announcement date. I find a both statistically and economically significant association between smoke exposure and CAR. According to the coefficient estimate in column 2, a one standard deviation (16-day) increase in annual smoke exposure is associated with a 21-basis point decrease in [-1, 1] day CAR. These findings suggest that market participants do not fully anticipate the diffuse effects of physical climate risk.

Table 8 Wildfire Smoke and Earnings Announcement Return

This table presents the effect of wildfire smoke on earnings announcement return. The sample is restricted to observations with a stock price of at least five dollars. In column 1, the dependent variable is the difference between actual earning and mean analyst forecast earnings divided by the month-end stock price before the earnings announcement. In column 2, the dependent variable is 3-day cumulative abnormal returns around the annual earnings announcement date. The interested independent variable is SmokeDays, which equals the number of days the county where a firm headquartered are covered by wildfire smoke. Both columns include firm fixed effects and year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1) Earning Surp	(2) CAR [-1, 1] (%)
SmokeDays	-0.0189***	-0.0134**
	(0.0053)	(0.0063)
WildFire	-0.0020***	-0.0034**
	(0.0007)	(0.0016)
Wind Speed	0.9849	0.1175
	(0.7249)	(0.5103)
Wind Direction	0.0185	0.0194
	(0.0132)	(0.0132)
Temp above 30	-0.0199	-0.0004
	(0.0136)	(0.0055)
Temp below 0	-0.0085	0.0127**
	(0.0085)	(0.0051)
GDP Percap	10.3087*	2.6422**
	(5.3994)	(1.1663)
Precip	-0.0002	-0.0010***
	(0.0002)	(0.0003)
Observations	22,010	23,263
Adjusted R-squared	0.4614	0.0439
Fixed Effect	Firm, Year	Firm, Year

5.6. Disclosure of Climate Change Exposure

Accounting theory suggests disclosure improves market efficiency (Gao, 2008). Climate change disclosure may moderate the impairment of wildfire smoke exposure on operating income and market returns. I provide insight into this discussion by examining whether firms and the financial market benefit from voluntary climate-change disclosure. The literature finds that voluntary disclosure of non-financial information is associated with positive feedback from the market. For example, firms enjoy a lower cost of equity after voluntarily disclosing their corporate social responsibility (CSR) activities (Dhaliwal et al., 2011). The benefits of issuing voluntary disclosure include improving the information environment and better internal control (Cheng, Ioannou, and Serafeim, 2013).

I first examine the moderating role of climate-change disclosure on the adverse effect of wildfire smoke exposure on operating income. My proxy of climate change disclosure comes from Sautner et al. (2020), who apply a machine-learning approach to extract firm-level climate change exposure (*CC_expo*) from conference call transcripts. The analysis is restricted to the sample of firms with non-missing climate change exposure during the annual earnings conference calls. I divide the sample into subsamples of firms based on the climate change disclosure in year t-1. Columns 1 and 2 of Table 9 present the effect of smoke exposure on firms' operating income with different levels of voluntary disclosure. I find no evidence that the levels of voluntary disclosure of climate change risk are associated with operating loss from wildfire smoke. This result alleviates the concerns of self-selection bias: Firms with higher *CC_expo* may have lower wildfire smoke exposure.

I then examine whether climate change disclosure is associated with less negative feedback from the financial market. Columns 3 and 4 of Table 9 presents the effects of smoke exposure on market reactions with different levels of voluntary disclosure. I find that the negative association between the market reaction to earnings announcements and smoke exposure is only significant among firms with low climate change disclosure. This result suggests that more voluntary climate change disclosure increases firms' information environmental, and leads to better capital market efficiency.

Table 9 Voluntary Disclosure and Effects of Wildfire Smoke

This table presents the effect of wildfire smoke on firm performance and the stock market with different levels of voluntary climate change disclosure. In columns 1 and 2, the dependent variable is operating income before depreciation divided by total assets in year t-1. In columns 3 and 4, the dependent variable is CAR [-1, 1] around the annual earnings announcement date. The proxy for climate change disclosure is the proportion of climate-exposure keywords from Sautner et al. (2020) in year t-1, and the sample is restricted to firms with climate change disclosure. Columns 1 and 3 include the subsample with above-median climate change disclosure, and columns 2 and 4 include the sample with below-median climate change disclosure. All columns include firm fixed effects and year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1)	(2)	(3)	(4)
	Operating Income/Asset (%)		CAR [-1, 1] (%)	
	High Disclosure	Low Disclosure	High Disclosure t-	Low Disclosure
SmokeDays	-0.0278**	-0.0211***	0.0073	-0.0322**
	(0.0137)	(0.0056)	(0.0074)	(0.0140)
WildFire	-0.0041**	-0.0016	-0.0058***	-0.0033***
	(0.0019)	(0.0011)	(0.0020)	(0.0011)
Wind Speed	1.0965	-0.1753	0.5182	-0.4855
	(0.7441)	(0.7729)	(0.6088)	(0.8685)
Wind Direction	-0.0099	-0.0118	-0.0037	-0.0469***
	(0.0095)	(0.0231)	(0.0136)	(0.0162)
Temp above 30	0.0078	-0.0162	-0.0101	0.0278*
	(0.0145)	(0.0249)	(0.0102)	(0.0160)
Temp below 0	-0.0062	-0.0098	0.0086**	0.0137
	(0.0129)	(0.0135)	(0.0042)	(0.0103)
GDP Percap	8.3576**	8.1881	2.4117	2.0331
	(3.2939)	(5.9472)	(1.8602)	(2.7069)
Precip	-0.0003	-0.0013**	-0.0000	-0.0013***
	(0.0004)	(0.0005)	(0.0004)	(0.0005)
Z test of Difference	-0.4527		2.4944**	
Observations	10,685	10,672	9,891	9,998
Adjusted R-squared	0.8107	0.8143	0.0826	0.0703
Fixed Effect	Firm, Year	Firm, Year	Firm, Year	Firm, Year

5.7. Adaptation Behaviors

In response to increasing climate-change risk, firms are pursuing mitigation strategies. For example, firms are adjusting supply chains to reduce exposure to heat waves (Pankratz and Schiller, 2020). When long-term abnormal temperatures decrease local demand, firms are likely to close establishments (Jin et al., 2021). Relative to temperature change, smoke exposure is less salient and predictable. I expect firms to engage in soft adaptation, such as outsourcing production across facilities, rather than permanent changes.

To identify firms' adaptation behavior, I examine the association between smoke exposure and plant-level production activities. I collect plant-level information from the Toxic Release Inventory (TRI) database. The database covers manufacturing plants (SIC from 2000 to 3999) with more than ten full-time employees. Instead of using headquarters smoke exposure, I use each plant's county location to determine its annual smoke exposure. I use two measures as proxies for a plant's production activities. Following Akey and Appel (2021), I use the production ratio reported in the TRI database to construct the first production measure. The TRI reports the change in production associated with each chemical. For example, if a chemical is generated in producing product p, the TRI will report a production ratio at year *t* for the chemical as $\frac{Quantity\ Produced_{p,t}}{Quantity\ Produced_{p,t-1}}$. I calculate the cumulative production quantity by setting the production quantity as one in the first year that a plant reports its chemical production ratio and multiplying forward each year using the following equation:

$$Production\ Quantity_{p,t} = \prod_{t\neq 1}^{t} 1 \times (\ Production\ Ratio_{p,t})$$

For plants that emit multiple chemicals, I take the average of all cumulative production to get a plant-year measure. The second measure of production is total toxic waste emitted by a plant.

Table 10 presents the effect of plant-level smoke exposure on production activities. On average, I find no effect of annual smoke exposure on plant-level production activities. However, a plant's smoke exposure leads to reduced production activities after experiencing a continuously high level of smoke exposure, measured by the quartile of smoke exposure in the past five years. These results suggest that firms learn from the long-term experience of smoke exposure.

Table 10 Plant-level Adaptation to Smoke Exposure

This table presents the effect of wildfire smoke on plant-level production activities. In column 1, the dependent variable is the average quantity production from each chemical. In column 2, the dependent variable is the logarithm of total pollutant emissions. The interested independent variable is SmokeDays, which equals the number of days the county where a plant is covered by wildfire smoke. SmokePre5 Q4 equals 1 if a plant experienced 4^{th} quartile of smoke days from year t-5 to year t-1. Both columns include plant fixed effects and year fixed effects. Regressions are weighted by the plant's county-level population each year. Robust standard errors that are clustered at the plant state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1) Production Quantity	(2) Log (Total Emissions)
Plant SmokeDays	0.0001	-0.0008
	(0.0002)	(0.0007)
Plant SmokeDays *SmokePre5 Q4	-0.0014*	-0.0039***
	(0.0007)	(0.0012)
SmokePre5 Q4	0.0392	0.1793***
	(0.0306)	(0.0435)
Wind Speed-Facility	0.0321	0.0592
	(0.0264)	(0.1027)
Wind Direction-Facility	0.0003	0.0005
	(0.0003)	(0.0014)
WildFire-Facility	-0.0000*	-0.0000
	(0.0000)	(0.0000)
Temp above 30-Facility	0.0002	-0.0007
	(0.0001)	(0.0006)
Temp below 0-Facility	-0.0002	-0.0014**
	(0.0002)	(0.0006)
GDP Percap-Facility	-0.0007	0.0147
	(0.0140)	(0.0329)
Precip-Facility	0.1341	0.6554*
	(0.1432)	(0.3878)
Observations	64,456	56,207
Adjusted R-squared	0.1206	0.9158
Fixed Effect	Plant, Year	Plant, Year

5.8. Wildfire smoke and Supply-chain Disruptions

The cross-sectional tests suggest that wildfire smoke exposure affects a firm's operating performance by lowering productivity among skilled workers. It is possible that reduced consumer demand when exposed to wildfire smoke also contributes to the observed effects. Public firms' customers may be located far from supplier headquarters, but significant correlations may exist between a firm's smoke exposure and its customers' smoke exposure.

I use three measures to identify the effect of smoke exposure on customer demand. The first measure captures major customers' smoke exposure using customers identified by Compustat's segment data. I use counties where major customers are headquartered to measure customer smoke exposure. Columns 1 and 2 of Table 11 present the results. Column 2 excludes observations if major customers operate in geographically dispersed industries. I find no significant association between major customers' smoke exposure and a firm's operating performance.

The second measure follows Srinivasan, Lilien, and Rangaswamy (2002) and uses the four-digit SIC code to determine whether a firm belongs to the business-to-business (B2B) or business-to-consumer (B2C) industry. If a firm's smoke exposure captures its customer exposure, the effects on operating performance should be stronger in B2C industries (Jin et al., 2021). Columns 3 and 4 of Table 11 present the results. I find no significantly different effect of smoke exposure between firms in the B2B industry or B2C industry.

The third measure relies on vertical integration data from Frésard, Hoberg, and Phillips (2019). This data utilizes text-based product information to identify a firm's potential suppliers and customers. I construct aggregated customer (supplier) smoke exposure by summing each potential customer (supplier) smoke exposure weighted by relatedness scores. Columns 5 and 6 of Table 11 include potential customer (supplier) smoke exposure in equation (1). While I find potential customer (supplier) smoke exposure leads to lower operating performance, the coefficient estimates of a firm's smoke exposure change little.

This evidence that supply-chain disruptions from wildfire smoke lead to lower operating performance supplements Pankratz and Shiller (2020), who find that operating performance decrease when suppliers experience abnormal temperatures and floods. In all columns, focal firms' wildfire smoke exposure remains significantly associated with operating performance. Therefore, I conclude that my estimate of the effect of wildfire smoke exposure on firm performance is mostly driven by changes in employee productivity.

Table 11 Wildfire Smoke and Supply Chain

This table presents the effect of wildfire smoke on operating income through supply-chain disruptions. The dependent variable is operating income before depreciation divided by total assets in year t-1. The interested independent variable is SmokeDays, which equals the number of days the county where a firm headquartered are covered by wildfire smoke. Columns 1 and 2 include the smoke exposure days of major customers in the segment reporting. Column 2 excludes observations if customers operate in dispersed industries. Columns 3 and 4 include smoke days interact with an indicator of B2B or B/C industries. Columns 5 and 6 include smoke exposures of potential customers and suppliers. Weather characteristics and firm characteristics are included in all regressions. All columns include firm fixed effects and year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Operating Income/Asset (%)					
		Exclude Dispersed Customers				
SmokeDays	-0.0198**	-0.0232**	-0.0168**	-0.0223***	-0.0172***	-0.0176***
	(0.0092)	(0.0098)	(0.0066)	(0.0073)	(0.0041)	(0.0043)
Customer SmokeDays	0.0143	0.0205				
	(0.0108)	(0.0130)				
SmokeDays*B2B			-0.0035			
			(0.0080)			
SmokeDays*B2C				0.0069		
				(0.0102)		
Potential Customer SmokeDays					-0.0084***	
					(0.0027)	
Potential Supplier SmokeDays						-0.0062**
						(0.0026)
Customer ROA	3.6407	-0.8086				
	(2.5999)	(2.8374)				

Table 11 (cont'd)

Potential Customer ROA					3.9708***	
					(0.8778)	
Potential Supplier ROA						2.8006***
						(0.8429)
Observations	31,653	28,742	30,977	30,977	31,196	31,196
Adjusted R-squared	0.8033	0.8102	0.7977	0.7977	0.7980	0.7979
Weather Control	Yes	Yes	Yes	Yes	Yes	Yes
Firm Control	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year

CHAPTER 6: ROBUSTNESS TESTS

6.1. Firms with Dispersed Employees

In this section, I perform additional analyses to identify the potential measurement error biases. First, I examine the size of firm-specific measurement errors due to dispersed employees. I identify the locations of plants, units, subsidiaries, and branches from the LexisNexis corporate affiliation database. I consider a firm to have dispersed employees if at least one affiliation has more than 15% of employees relative to the corporate number of employees and locates in different counties as the headquarters. Table 12 presents the results. Column 1 includes all matched observations and column 2 excludes firms with dispersed employees. Consistent with the baseline results, I find a larger magnitude of smoke exposure on operating income when excluding firms with dispersed employees. Columns 3 and 4 replace operating income with net income divided by the book value of assets at year t-1 as an alternative performance measure. I find that smoke exposure also leads to decreased net income.

Table 12 Effect of Dispersed Operation

This table presents the robustness test of the effect of wildfire smoke on firm performance. The sample contains all affiliations (plants, units, subsidiaries, and branches) in the LexisNexis corporate affiliation database. *Dispersed Employee* is an indicator variable that equals 1 if any affiliation has 15% or more employees of the parent firms, and 0 otherwise. The interested independent variable is SmokeDays, which equals the number of days the county where a firm headquartered are covered by wildfire smoke. In columns 1-2, the dependent variable is operating income before depreciation divided by total assets in year t-1. In columns 3-4, the dependent variable is adjusted net income divided by total assets in year t-1. All columns include firm fixed effects and year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1)	(2)	(3)	(4)
	Operating Income/Asset (%)		Net Income/Asset (%)	
	Full Sample	Exclude Dispersed	Full Sample	Exclude Dispersed
SmokeDays	-0.0212**	-0.0238***	-0.0232**	-0.0247**
	(0.0092)	(0.0085)	(0.0096)	(0.0105)
Subsidiary SmokeDays	-0.0020	0.0052*	-0.0024	0.0039
	(0.0051)	(0.0030)	(0.0055)	(0.0051)
WildFire	-0.0015***	-0.0016*	-0.0016***	-0.0010*
	(0.0003)	(0.0009)	(0.0004)	(0.0006)
Wind Speed	0.9684**	0.8843**	1.6069**	1.9749**
	(0.4386)	(0.3821)	(0.6357)	(0.8049)
Wind Direction	0.0094	-0.0126	0.0034	-0.0158
	(0.0137)	(0.0121)	(0.0142)	(0.0213)
Temp above 30	-0.0168	-0.0159	-0.0168**	-0.0233***
	(0.0117)	(0.0130)	(0.0082)	(0.0082)
Temp below 0	-0.0174	-0.0182**	-0.0098	-0.0126
	(0.0112)	(0.0083)	(0.0119)	(0.0092)
GDP Percap	12.2306***	10.6583***	12.7701***	11.6513***
	(4.5402)	(3.4945)	(3.4717)	(3.0759)
Precip	-0.0001	-0.0003	-0.0004	-0.0008*
	(0.0004)	(0.0003)	(0.0005)	(0.0004)
	(1.8213)	(3.3265)	(3.2794)	(4.3102)
Observations	13,863	9,933	14,162	10,152
Adjusted R-squared	0.7352	0.7528	0.5952	0.5927
Fixed Effect	Firm, Year	Firm, Year	Firm, Year	Firm, Year

6.2. Portfolio Returns

While I find that higher smoke exposure is associated with greater earnings surprise and negative market reactions, it is possible that there is no long-term effects of smoke exposure on the stock return. I then explore whether the diffuse effects of climate change have long-term market effects by exploring the association between wildfire smoke exposure and long-term buy-and-hold abnormal returns (BHAR). I assign firms into four quartiles based on the number of days a firm experiences smoke coverage as of year t-1. Panel A of Table 13 presents my findings. On average, a trading strategy of buying and holding firms in the lowest smoke exposure quartile and selling firms in the highest smoke exposure quartile in year t earns 6.6% abnormal annual returns over 12 months. In Panel B, I regress BHAR-3 month to BHAR-24 month on year t-1 smoke coverage and control for firm fixed effects. The results are consistent with Panel A.

Table 13 Portfolio Returns

This table presents the average portfolio buy-and-hold abnormal return (BHAR) for up to 24 months. The portfolio is sorted by quartile of smoke days in the previous year. For each firm i, $BHAR_{i(t,T)} = \prod_{t=0}^{T}(1 + R_{it}) - \prod_{t=0}^{T}(1 + E[R_{it}|X_t])$, where R_{it} is monthly return, and $E[R_{it}|X_t]$ is value-weighted monthly market return. The holding period starts from the month after the fiscal year-end. Panel A presents the equal-weighted portfolio BHAR, and panel B presents regression results of different time-horizon BHAR. All regressions include firm fixed effects. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

Panel A: Trading Portfolio

Smoke Days	3 Month	6 Month	9 Month	12 Month	18 Month	24 Month
1	0.007	0.024	0.065	0.102	0.053	0.102
2	-0.007	0.003	0.032	0.048	0.044	0.102
3	-0.006	-0.012	-0.001	0.021	0.048	0.100
4	0.001	-0.002	0.009	0.036	0.039	0.089
Quartile 1 - Quartile	0.005	0.026***	0.056***	0.066***	0.014	0.014

Panel B: Regression Result

	(1)	(2)	(3)	(4)	(5)	(6)
			$BHAR_{i(t,T)}$			
	3 Month	6 Month	9 Month	12 Month	18 Month	24 Month
SmokeDays $_{t-1}$	-0.0004	-0.0016***	-0.0034***	-0.0034***	-0.0021***	-0.0035***
	(0.0003)	(0.0004)	(0.0005)	(0.0006)	(0.0006)	(0.0007)
Leverage	-0.0977***	-0.1717	-0.2119**	-0.3286**	-0.3931***	-0.5968***
	(0.0293)	(0.1066)	(0.1040)	(0.1375)	(0.0583)	(0.0692)
M/B	0.0269***	0.0556***	0.0919***	0.1350***	0.1931***	0.2519***
	(0.0026)	(0.0036)	(0.0057)	(0.0052)	(0.0073)	(0.0121)
Log(MVEQ)	0.0472***	0.0629***	0.0767***	0.1029***	0.1528***	0.2151***
	(0.0045)	(0.0058)	(0.0065)	(0.0095)	(0.0114)	(0.0168)
Observations	33,634	33,634	33,634	33,634	32,773	31,912
Adjusted R-squared	0.0922	0.0808	0.0920	0.1097	0.2235	0.2118

6.3. Unobservable Wildfires

While all regressions control for the number of days that a firm's headquarters experienced wildfires, unobservable wildfires in nearby counties could associate with both wildfire smoke and corporate performance. To rule out this alternative explanation, I exclude firms from analysis if they are headquartered in states that experienced significant wildfires. Significant wildfires are defined as wildfires that caused at least $10 million in property damages according to NOAA.

The analysis results are presented in Table 14. Column 1 includes firm and year fixed effects. Column 2 further includes industry by year fixed effects to control for unobservable industry trends. For both models, I find the coefficient estimate of wildfire smoke is similar to the baseline tests. This result alleviates the concern that the negative association between wildfire smoke and corporate performance is driven by unobservable wildfire damages.

Table 14 Exclude States with Significant Wildfires

This table presents the robustness test of the effect of wildfire smoke on firm performance. State-years with significant wildfires are excluded from the sample. Significant wildfires are wildfires that caused more than $10 million property damage. The interested independent variable is SmokeDays, which equals the number of days the county where a firm headquartered are covered by wildfire smoke. Columns 1 includes firm fixed effects and year fixed effects, and columns 2 includes firm fixed effects and industry by year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1)	(2)
	Operating Income/Asset (%)	
SmokeDays	-0.0208***	-0.0187**
	(0.0075)	(0.0077)
WildFire	-0.0335*	-0.0240*
	(0.0191)	(0.0131)
Wind Speed	0.9154	0.8792
	(0.8462)	(0.8093)
Wind Direction	-0.0290*	-0.0254
	(0.0150)	(0.0205)
Temp above 30	-0.0072	0.0114
	(0.0153)	(0.0089)
Temp below 0	-0.0116	-0.0018
	(0.0137)	(0.0090)
Precip	10.7151**	8.0342**
	(4.1145)	(3.7498)
GDP Percap	-0.0006	0.0004
	(0.0005)	(0.0005)
Observations	25,375	24,659
Adjusted R-squared	0.7891	0.8046
Fixed Effect	Firm, Year	Firm, Ind by Year

6.4. Smoke Intensity

In the main analysis, the measure of smoke exposure is the number of days that a firm's headquarters is fully covered by smoke plumes. One drawback of this measure is that it does not capture the smoke intensity. To overcome this drawback, I obtain daily AQI data from the EPA and compare the differences in AQI between smoke days and non-smoke days. I first calculate the average monthly AQI in each county during smoke days (e.g., June 2018), and non-smoke days in the previous five years (e.g., June of 2013 - 2017). I then compare monthly AQI between smoke days in each month and non-smoke days in the same month over the previous five years. If the AQI on smoke days is lower than on non-smoke days, I code smoke intensity as zero. Otherwise, smoke intensity is the difference between the two average monthly AQIs. Finally, I aggregate the monthly smoke intensity into an annual measure by averaging the monthly smoke intensity.

This measurement of smoke intensity assumes that wildfire smoke contributes to all increases in AQI during smoke days. However, the value of AQI is calculated from observed levels of several air pollutants ($PM_{2.5}$, PM_{10}, Ozone, and SO_2). The main pollutant in wildfire smoke is $PM_{2.5}$. To better capture the effect of wildfire smoke, I follow Deryugina et al., (2019) in using the instrumental variables (IV) approach. After controlling for other wildfire activities and other weather characteristics, I argue that a county's wind speed and wind direction are unrelated to corporate performance except through their influence on wildfire smoke intensity.

The estimate of two-stage least squares is presented in Table 15. I find that wind speed significantly predicts smoke intensity (F = 4.10). Moreover, higher smoke intensity leads to significantly lower corporate performance: A one-standard-deviation increase in smoke intensity (12.5) leads to a 73-basis point loss of annual ROA. In columns 3 and 4, I scale smoke intensity by the number of smoke days, and I find similar estimation results.

Table 15 Smoke Intensity: An Instrumental Variable Approach

This table presents the effect of wildfire smoke on firm performance using the instrumental variable approach. The instrumental variables are wind speed and wind direction following Deryugina et al., (2019). In column 1, the instrumented variables are Smoke Intensity, which equals the annual average differences in air quality index between smoke days and non-smoke days. In column 3, the instrumented variable is Smoke Intensity/Smoke Days, which equals the smoke intensity scaled by the number of smoke days. All columns include firm fixed effects and year fixed effects. Regressions are weighted by county-level population each year. Robust standard errors that are clustered at the state level are reported in the parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels using two-tailed tests, respectively.

	(1) Smoke Intensity	(2) Operating Income/Asset	(3) Smoke Intensity/	(4) Operating Income/Asset
	First Stage	*Second Stage*	*First Stage*	*Second Stage*
Wind Speed	-13.2548**		-4.2424***	
	(5.8540)		(1.1813)	
Wind Direction	0.1416		0.0346**	
	(0.1054)		(0.0130)	
F-test (p-value)	*4.10*		*21.56 (<*	
Smoke Intensity		-0.0583*		
		(0.0310)		
Smoke Intensity/Smoke Days				-0.1920*
				(0.1033)
WildFire		-0.0017		-0.0010
		(0.0011)		(0.0009)
Temp above 30		-0.0018		-0.0021
		(0.0111)		(0.0126)
Temp below 0		0.0068		0.0046
		(0.0085)		(0.0087)
GDP Percap		5.6741***		4.6675**
		(2.0119)		(2.3109)
Precip		-0.0002		-0.0000
		(0.0004)		(0.0005)
		(2.4445)		(2.4770)
Under-identification test				
(Kleibergen-Paap rk LM statistic)				
(p-value)		*5.303 (0.0705)*		*8.284 (0.0159)*
Observations	30,384	30,384	30,384	30,384
Adjusted R-squared		0.1844		0.1851
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year

CHAPTER 7: CONCLUDING REMARKS

This paper examines the effects of climate change on US corporate performance. Unlike prior studies that use abnormal temperatures or localized natural disasters as proxies for climate change, this paper proposes wildfire smoke as a new measure of climate change. The effects of wildfire smoke are far-reaching and hard to predict. I find wildfire smoke exposure leads to decreased corporate performance.

Wildfire smoke exposure has a stronger adverse effect on firm performance among firms most reliant on human capital. Although extant studies find that economies in developed countries are resistant to extreme temperatures, high reliance on human capital makes these economies more vulnerable to wildfire smoke. Moreover, smoke events are not as salient as temperature changes and natural disasters, making it hard for market participants to price its effect on corporate performance absent adequate disclosure.

Finally, this paper explores whether firms and investors benefit from climate-change disclosure. Using firm's voluntary climate-change disclosure in conference calls, I find that higher climate-change disclosure moderates the negative association between wildfire smoke exposure and market reaction to earnings announcements. This association may incentivize investors to require more climate-change disclosure and policy implication for regulators.

APPENDICES

APPENDIX A

Variable Definitions

Table A.1 Variable Definitions

This table presents the definition of all variables in this paper. I thank Srinivasan, Lilien, and Rangaswamy (2002) and Frésard, Hoberg, and Phillips (2019) for providing their data. All other data is publicly available/available through subscription.

Variable	Definitions
Operating Income/Asset	Operating income before depreciation divided by the total book value of assets in year t-1
Operating Expense/Asset	Total operating expense divided by the total book value of assets in year t-1
Sales/Asset	Total sales revenue divided by the total book value of assets in year t-1
CAR [-1, 1]	Three-day cumulative abnormal return around annual earnings announcement date using Fama-French 3-factor model.
Earning Surp	The difference between (Actual EPS - Forecasted EPS)/Share Price. The share price in month-end before the annual earnings announcements.
Net Income/Asset	Net income divided by the total book value of assets in year t-1
SmokeDays	The number of days that a county is fully covered by wildfire smoke
Climate Change Disclosure	The data is provided by Sautner, Van Lent, Vilkov, and Zhang (2020), who construct firm-level voluntary disclosure of climate change exposure from earnings conference calls. The measures equal the frequency of climate change bigrams, scaled by the total number of bigrams in the transcript of each year.
WildFire	The number of days that a county has wildfires each year
GDP Percap	The natural logarithm of county-level GDP per capita in each year
Wind Direction	The average wind direction based on a county's centroid coordinate, with zero corresponding to wind blowing from the north and higher values corresponding to compass directions clockwise.
Wind Speed	The average wind speed based on a county's centroid
Temp above 30	The number of days a county's centroid has an average temperature of 30^{o}C or above
Temp below 0	The number of days a county's centroid has an average temperature of 0^{o}C or below
Precip	Annual precipitation measured at a county's centroid

Table A.1 (cont'd)

R&D	R&D expenditures divided by the total book value of assets
Leverage	Firm leverage, total liability divided by the total book value of assets
Sales Growth	Difference between current year sales revenue and previous year sales revenue divided by previous year sales revenue
M/B	The market value of equity and book value of liability divided by book value of assets
PPE/Asset	The net value of property, plant, and equipment divided by the total book value of assets in year t-1
Tobin's Q	Book value of liabilities plus the market value of equity divided book value of assets
R&D/Emp	R&D expenditures (in millions) per employee; this measure is restricted to firms with positive R&D expenditures.
Labor Cost	SG&A expenditures (in millions) exclude R&D expenses per employee
Labor Skills	The industry labor skill index for industry i is calculated as $\sum_{j=1}^{O}(\frac{E_{ji}}{E_i} * Z_j)$, where Eji is the number of employees in an industry i working in occupation j, Ei is the total number of employees in industry i, and O is the total number of occupations in the industry i
Log (Total Emission)	The natural logarithm of total toxic releases (measured in pounds) from TRI for each plant
Production Quantity	The accumulated production following Akey and Appel (2021). Accumulated production= $\prod_{t\neq 1}^{t}(\,Production\ Ratio_{p,t})$, missing ratios are replaced by 1.
SmokePre5 Q	The quartile of smoke days that a plant experienced from year t-5 to year t-1. SmokePre5 Q4 equals 1 if a plant experienced 4th quartile of smoke days from year t-5 to year t-1, and 0 otherwise.
Customer SmokeDays	The number of days a major customer's headquarters county is covered by wildfire smoke. Major customers data come from segment reporting.
B2B (B2C) Industry	Business-to-Business (Business-to-consumer) industry indicator that follows Srinivasan, Lilien, and Rangaswamy (2002)
Potential Customer (Supplier) SmokeDays	The number of days a firm's potential customers and suppliers are covered by wildfire smoke, weighted by relatedness scores. Potential customers (suppliers) are identified by the text-based vertical integration data from Frésard, Hoberg, and Phillips (2019).

Table A.1 (cont'd)

Dispersed Employee	An indicator that equals to 1one if any subsidiary or plant that located in different counties from headquarters and has 15% or more employees relative to total corporate employees

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