What Lies Beneath the Haze?
Wildfire Smoke and Industrial Pollution

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Abstract

We study whether industrial plants exploit wildfire smoke episodes as cover to increase emissions. Using a difference-in-differences approach, we find that relative to air quality monitors without proximate industrial plants, those located near industrial plants record a significantly larger increase in SO_2 concentrations from non-smoke to smoke days, consistent with plants strategically timing emissions to coincide with wildfire smoke. At the same time, satellite-based thermal infrared radiation indicates intensified plant activity, pointing to opportunistic increases in production rather than coincidental factors. The emission response to wildfire smoke vanishes on weekends and holidays but is stronger among plants with more flexible production capacity or operating in financially distressed industries, reinforcing the role of deliberate operational choices under economic incentives. Moreover, the extent of the response is affected by local regulatory monitoring, suggesting that enforcement capacities moderate firms' incentives to pollute strategically. Overall, our findings reveal that wildfires not only degrade air quality directly but also create opportunities for industrial polluters to conceal emissions, underscoring the need for regulatory frameworks that anticipate and deter such opportunistic behavior.

Keywords: Opportunistic Pollution; Air pollution Monitoring; Wildfire Smoke; Thermal Infrared Radiation

JEL Codes: Q53; Q58; L23; Q54

1. Introduction

Recent years have witnessed a rapid increase in the intensity, frequency, and geographic reach of wildfires, due to the accelerated pace of global warming (Burke et al., 2023; Griffin et al., 2023). Smoke from wildfires carries a substantial amount of pollutants into the air, including fine particulate matter ($PM_{2.5}$), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and carbon monoxide (CO). Notably, the pollution signature (i.e., pollutant mix) of wildfire smoke closely resembles that of industrial emissions from the private sector, raising important questions about the implications for environmental oversight. This paper examines whether wildfire smoke hinders regulatory monitoring of industrial polluters, thereby undermining their incentives to adopt more sustainable production practices. In doing so, we shift the focus from the well-documented adverse consequences of wildfire smoke—such as decreased public health, elevated mortality, and economic disruptions (e.g., Borgschulte et al., 2024; Burke et al., 2021; Johnston et al., 2021; Qiu et al., 2024; Wang et al., 2021)—to a less explored but critical challenge at the intersection of environmental regulation and climate-induced natural disasters.

There are several reasons why plants may exploit wildfire smoke coverage to "hide" their pollutant emission. First, from a technical perspective, ambient air quality monitoring systems operated by regulators cannot distinguish between criteria pollutants carried by wildfire smoke and those from industrial sources. In addition, wildfire smoke reduces visibility (Koch et al., 2021), limiting local residents' ability to visually monitor and report excessive industrial pollution. These factors may create temporary opportunities for plants to increase emissions—through higher production or reduced abatement—without provoking backlash from stakeholders, which is often triggered by visible environmental harm

(Flammer, 2013; Krueger et al., 2020). Supporting this conjecture, the U.S. Environmental Protection Agency (EPA) also acknowledges that regulated polluters (and even local regulators) may lack incentive to control pollution during periods when exceptional events (such as wildfires) drastically raise air pollution.[1]

Second, wildfire events have become very frequent around the globe (Burke et al., 2023). In the United States (U.S.), wildfire smoke now affects 90% of counties and is present on one out of seven days for the average county. The recurring and widespread presence of wildfire smoke could make it a plausible disguise for excessive industrial emissions, particularly because pollution reduction activities (e.g., desulfurization) can be costly. For example, prior research finds find that firms cut abatement spending to report higher profitability or conserve cash flow (Thomas et al., 2022; Xu and Kim, 2022) and increase pollution when monitoring intensity declines (Agarwal et al., 2023; Zou, 2021).

Nonetheless, several considerations suggest that industrial pollution may instead decline during wildfire smoke events. Prior studies find that individuals respond to air pollution by reducing labor supply and outdoor activities (Neidell, 2009; Hanna and Oliva, 2015; Hoffmann and Rud, 2024).[2] Beyond labor supply effects, air pollution also hinders worker productivity as pollutants such as $PM_{2.5}$ penetrate indoors (Chang, Zivin, Gross, and Neidell, 2016, 2019; He, Liu, and Salvo, 2019). Thus, it is possible that wildfire smoke

[1] In a recent report, the EPA states that they "expect daily air quality values associated with exceptional events to be anomalously higher than values on normal days during online periods because of the exceptional event pollution and the lack of regulated entity and state and local government incentive to hide elevated pollution from the EPA during these events" (U.S. Environmental Protection Agency, 2025, p.34). An exceptional event is an unusual or naturally occurring event (e.g., wildfires, dust storms from high winds) that causes significant air pollution but is not reasonably controlled by local regulators. The EPA exclude air quality data recorded during concurrent exceptional events when evaluating local compliance with the National Ambient Air Quality Standards.

[2] The reduction in labor supply during air pollution may be driven by the need to care for one's own health or venerable family members. For instance, the California Family Rights Act allow employees affected by wildfires to apply for leave of absence. For details, see: https://www.callaborlaw.com/blog/socal-wildfires-guidance-for-employers-supporting-their-workforce-through-difficult-times.

decreases employees' labor supply and output, leading to a lower production intensity and, ultimately, less pollution from industrial sites. Taken together, whether wildfire smoke creates a "pollution window" for industrial plants is an empirical question we take to the data.

Ideally, detecting opportunistic emissions under wildfire smoke would involve tracking plants' direct emissions at a relatively high-frequency level, e.g., a daily level. One would then compare changes in emission levels between days with and without wildfire smoke coverage. However, such data is not publicly available because the Environmental Protection Agency (EPA) typically tracks and discloses plants' toxic emissions on an annual basis. To address this empirical challenge, we take an alternative approach by using the criteria pollutant concentration data recorded by EPA monitoring devices (EPA monitors hereafter). Further, we exploit variations in the monitors' geographic distance to industrial areas.[3] This variation allows us to compare the pollution readings from monitors in industrial areas and those with no nearby plants during wildfire smoke days and non-smoke days, thereby generating a difference-in-difference style comparison.

Basing our analysis on a near-universe sample of EPA sulfur dioxide (SO_2) monitors that experience wildfire smoke coverage between 2011 and 2023, we present three sets of main findings. First, there is an increase in SO_2 readings from monitors with nearby industrial plants on smoke days as opposed to monitors without nearby plants. Compared with monitors without nearby industrial plants, monitors with one additional plant within a one-mile radius have an additional 0.014 increase in so-2 concentration from a non-smoke day to a smoke day, or a 24.6% increase relative to the effect of wildfire smoke itself on SO_2 concentration. This difference in SO_2 reading response to wildfire smoke cannot be explained by differences in

[3] As we later show, there is substantial variation in monitors' distance to industrial areas, and co-location with plants leads to a sizable increase in the concentration of pollutants recorded by a monitor.

weather conditions, such as same-day temperature or precipitation. In addition, we flexibly control for short-term trends in local factors that affect pollution (e.g., atmospheric conditions) by including monitor-by-year-week fixed effects. The effect of nearby plants on pollution response to wildfire smoke quickly dissipates as we focus on plants above three miles from the monitoring station. The high sensitivity of SO_2 readings' response to plant co-location over such a short distance is consistent with the quick dilution of air pollution as it travels away from its sources.[4]

Second, we conduct several tests to link the SO_2 reading response near plants to their opportunistic adjustment of capacity utilization. Most production activities consume energy and simultaneously emit thermal infrared radiation (TIR). Using satellite-based plant TIR as a measure of capacity utilization, we document an unusually high plant-level TIR when the plant is under wildfire smoke coverage, suggesting that these plants temporarily increase their production and pollute more under wildfire smoke. In addition, we examine the SO_2 concentration response on workdays versus non-workdays and document a stronger increase in SO_2 readings on workdays but a null result during non-workdays. Furthermore, we build on the findings of Zou (2021) and identify plants with higher production flexibility, which enables them to quickly adjust capacity utilization to exploit the cover of wildfire smoke. We document that plants with high production flexibility are responsible for most of the SO_2 increase during wildfire smoke coverage. Together, these results provide strong evidence that plants temporarily increase their capacity utilization on smoke days to exploit the emission window under wildfire smoke.

[4] https://semspub.epa.gov/work/HQ/100002484.pdf

Third, we explore the cross-sectional variation in the documented hidden pollution in relation to several local factors, primarily local environmental enforcement strictness and socioeconomic conditions. We find that plants are more likely to engage in this opportunistic behavior when nearby monitors operate at a higher frequency, likely because the pollution window created by wildfire smoke is more valuable to such closely watched plants. Meanwhile, the opportunistic behavior is effectively muted among plants located in counties that do not meet the EPA's national air quality standards, as such plants may worry that their pollution would lengthen local nonattainment status. Furthermore, we show that plants located in areas with greater tolerance of corporate environmental irresponsibility, high poverty ratios, high unemployment rates, or low population densities appear more likely to increase their pollution under wildfire smoke.

In a set of concluding analyses, we evaluate the robustness of the result of hidden pollution under wildfire smoke. Specifically, we conduct two placebo tests to evaluate whether our finding could be driven by chance by randomly assigning wildfire smoke dates within a given monitor–year and by scrambling the number of nearby plant counts. In both tests, we find that the true coefficient estimate for our variable of interest lies well above the far right of the distribution of the coefficient estimates based on placebo samples. We also examine hidden pollution from monitored plants by using other EPA-monitored pollutants (NO_2, $PM_{2.5}$, and Ozone), and we experiment with alternative regression specifications. Our main inferences remain similar.

This paper makes three main contributions to the literature. First, it adds to the emerging literature on the adverse effects of wildfire smoke, which has intensified significantly in the past two decades as a result of climate change (e.g., Burke et al., 2023;

Qiu et al., 2024). Burke et al. (2023) find that wildfire smoke increasingly contributed to U.S. PM2.5 levels from 2000 to 2022, slowing or reversing decades of air quality gains under the Clean Air Act. Qiu et al. (2024) estimate that by 2050, climate-driven wildfire smoke could cause up to 27,800 deaths per year. Using aggregated earnings data, Borgschulte et al. (2024) estimate that smoke exposure reduces quarterly earnings by 0.1% per day. Kong et al. (2024) explore the effect of wildfire smoke on the corporate world and find that more days of wildfire smoke are associated with lower operating performance due to its significant effect on employee health. While existing studies largely focus on the effects of wildfire smoke on individual health and labor market outcomes, our study explores the opportunistic behavior of the private sector's emission strategies.

Second, this paper adds to the literature that investigates organizations' evasive actions in response to tightening environmental regulations. Although costly pollution control activities generate public benefits, a growing number of studies show that firms have strong incentives to evade regulatory oversight. For example, Agarwal et al. (2023) and Vollaard (2017) document that firms discharge more pollution into the environment under the cover of darkness. Zou (2021) finds that more pollution comes from industrial areas when nearby monitors are turned off due to intermittent monitoring schedules. Other studies show that firms respond to environmental regulation by relocating their businesses to less regulated areas (Bartram et al., 2022), selling pollutive assets (Duchin et al., 2025), siting pollutive activities downwind or downstream (Morehouse and Rubin, 2021), and greenwashing (Tang et al., 2023). Local governments seeking to balance environmental regulation and economic activities reduce environmental monitoring by deactivating air monitoring devices when they anticipate low air quality (Mu et al., 2024) or by selectively enforcing tighter environmental standards on factories immediately upstream of water monitoring stations (He et al., 2020). Our paper complements this line of research by showing a potentially vicious circle of air pollution: plants emit more when air quality is already poor due to external reasons.

Last, our paper contributes to a growing literature that uses alternative data sources to unveil hidden socioeconomic activities. For instance, research has leveraged individual location data inferred from cell phone signals to study consumer behavior (Noh et al., 2025) and community response to lockdown during COVID-19 (Grantz et al., 2020). Other papers use taxi data or corporate jet flight data to infer information events (Bradley et al., 2024; Yermack, 2014). Among alternative data sources, satellite image data has been extensively used due to its high-frequency coverage and immutability to monitored persons or organizations. In addition to playing an instrumental role in environmental monitoring (e.g., Finer et al., 2018), satellite image data have been mined to track firm or macroeconomic performance (e.g., Mukherjee et al., 2021; Zhu, 2019). Our paper contributes to this stream of research by combining ground-level monitor data with satellite wildfire smoke and thermal radiation data to triangulate firms' disguised actions, expanding the types of satellite imagery that could be useful for future research.

2. Background

2.1. Public Monitoring in Environmental Regulation

To enforce environmental laws, the U.S. EPA mobilizes residents near pollution hotspots to help track and identify excessive pollution and violations, and local residents can report possible violations through formal channels. For example, the Enforcement and Compliance History Online (ECHO)—a data hub for all environment-related violations—operates an online platform through which residents can report suspected adverse environmental events.[5] Furthermore, the EPA reports that violations are often discovered through tips from the public and cites citizen complaints as one of the top triggers for its civil investigation into a regulated entity's compliance status.[6]

Residents can help track factory pollution in several ways. First, many types of plants, such as oil refineries or petrochemical plants, generate visible plumes of smoke or flares. Other types of toxic emissions often come with noxious-smelling fumes. A sudden increase in smoke or odor intensity around plants often provokes nearby residents, which in turn draws media coverage and the EPA's attention (e.g., Human Rights Watch, 2024). Second, residents often install their own air monitors due to a need for real-time air quality data or as an alternative data source to publicly reported air quality readings (e.g., The Allegheny Front, 2024). Such self-collected data can empower residents to respond to environmental risks by correlating industrial activities with observed data. As a result, local residential monitoring can be an effective way to deter excessive pollution (Jiang and Kong, 2024).

Smoke from wildfires significantly hinders residents' ability to track industrial pollution intensity. Severe wildfire smoke plumes reduce visibility, carry odor from the release of volatile organic compounds (VOCs), and increase readings of criteria pollutants. This deterioration in air quality makes it more challenging for residents to distinguish industrial air pollution from wildfire smoke through visual smoke, smells, or monitor readings. Thus, wildfire smoke creates a possible window during which plants can increase pollution while avoiding public backlash.

2.2. Incentives to Adjust Short-term Emissions

[5] https://echo.epa.gov/report-environmental-violations
[6] https://www.epa.gov/compliance/monitoring-compliance

Existing studies suggest that certain pollution control activities, such as desulfurization and selective catalytic reduction, can be costly due to the consumption of power or other materials (e.g., Agarwal et al., 2023; Zou, 2021). Take desulfurization as a more specific example. In addition to making a lump-sum capital expenditure required to install flue gas desulfurization system (i.e., SO2 scrubbers), plants incur daily operating costs including limestone reagent, waste disposal costs, labor, and maintenance. The U.S. Energy Information Administration estimates that in 2022, the average costs of existing flue gas desulfurization units per megawatt hour in the power sector include $2.36 for operation and maintenance and $108.15 for capital expenditure.

Managers tend to make pollution abatement decisions by weighing the benefits against the costs outlined above. A decrease in net benefits thus reduces plants' efforts to reduce pollution. More importantly for our study, plants can reduce their short-term pollution control efforts in the following ways. First, many end-of-pipe waste control devices are independent of the production process and can be temporarily turned on or off without disturbing plant production. This setup gives plants the flexibility to adjust their daily waste management operation expenses. Further, plants from certain industries often run at partial capacity in normal times and have room to adjust their capacity in response to future contingencies, such as demand shocks (Fine and Freund, 1990; Jordan and Graves, 1995) or changes in regulatory intensity (Zou, 2021).

Given the preceding discussion, we believe that wildfire smoke creates a pollution window for monitored plants, which also have the incentive and capacity to respond to this opportunity. We predict that plants with wildfire smoke coverage opportunistically increase their pollution.

3. Data and Empirical Design

3.1. Wildfire Smoke

We obtain wildfire smoke data from the Hazard Mapping System (HMS), maintained by the National Oceanic and Atmospheric Administration (NOAA). Since September 2005, the HMS has utilized high-resolution satellite imagery (from 375 meters to two kilometers, depending on the satellite) from the Geostationary Operational Environmental Satellites to generate daily wildfire smoke coverage for the contiguous United States. Beginning in 2011, the HMS introduced a classification scheme that categorizes wildfire smoke into light, medium, or heavy based on the visually inferred thickness from satellite images. Accordingly, our analysis employs wildfire smoke data spanning 2011 to 2023. The HMS uses advanced fire-detection algorithms to differentiate wildfire smoke from confounding sources, such as clouds, other air pollutants, gas flaring, and structural fires, while trained analysts perform quality-control reviews to remove false detections and ensure accurate plume classification.[7]

Figure 1 illustrates both the temporal and geographical distributions of wildfire smoke coverage. In Chart A, we count the number of days that each county is exposed to wildfire smoke in a year based on HMS plume data. We then compute the average across all counties in each year and plot the resulting time series. Between 2011 and 2020, the average number of county-level smoke days fluctuated moderately, ranging between 20 and 40 days per year. Beginning in 2021, however, wildfire smoke exposure increased sharply, with the annual average climbing from roughly 40 days in 2020 to more than 80 days in 2021, exceeding 120

[7] This dataset, which provides spatially and temporally explicit measures of smoke plume distribution, has become a standard source in scientific and economic research examining wildfire smoke exposure (e.g., Aguilera et al., 2021; Borgschulte et al., 2024).

days in 2022, and peaking at over 150 days in 2023. This pattern highlights the unprecedented escalation of wildfire smoke exposure in recent years compared with the preceding decade.[8]

Chart B of Figure 1 depicts the geographical distribution of the average annual smoke days over the sample period. Counties in the Midwest and Southern states exhibit substantially higher frequencies of smoke exposure than other regions, largely due to long-range transport of wildfire smoke from Canada under prevailing wind patterns (Gilbert, 2025; Wang et al., 2023; Yang et al., 2022).[9] This transboundary movement of wildfire smoke implies that most plants and monitoring stations in our sample are seldom located within the immediate burn areas of active wildfires. To construct daily smoke coverage at the EPA monitor level, we spatially overlay the HMS plume data with air monitor coordinates obtained from the EPA. Specifically, a monitor is classified as being under wildfire smoke coverage on a day if its geographic location falls within the boundaries of an HMS-identified smoke plume.[10]

3.2. EPA's Air Monitor and Plant Data

We draw on two data sources from the EPA to detect plants' concealed emissions during wildfire smoke episodes. The first is the EPA's Air Quality System (AQS) daily summary file, which reports criteria pollutants measured by EPA monitoring devices. This dataset includes monitor locations and daily pollutant concentrations for SO_2, NO_2, Ozone, and $PM_{2.5}$, calculated as the aggregation of 24 hourly observations from each monitor. For each monitor–

[8] Data from the Stanford Environmental Change and Human Outcomes Lab also indicate that per-capita exposure to wildfire smoke in the United States reached its highest level in 2023 since records began in 2006. The wildfire smoke that the United States has experienced in 2023 is mainly due to Canada's record wildfire season in the same year (https://www.climatecentral.org/climate-matters/wildfire-smoke-nationwide-health-risk-2023).
[9] To see the original fire locations and burned areas in Canada, please visit https://cwfis.cfs.nrcan.gc.ca/ha/nfdb?type=nbac&year=9999.
[10] In rare instances, a monitor situated near the boundary of a smoke plume may register coverage, while a proximate industrial plant lies outside the plume. In such cases, the monitor records wildfire smoke exposure even though the adjacent plant does not. In an untabulated robustness test, we follow Borgschulte et al. (2024) and intersect HMS plume data with county shapefiles from the U.S. Census Bureau to generate daily smoke exposure measures at the county-day level. Similar results ensue.

pollutant pair, we eliminate redundant daily entries by requiring measurements to be based on uniform sampling durations and standards. Moreover, we exclude monitor-days where raw sub-daily data were partially omitted from the daily summary due to "exceptional event" designations.

Our analysis primarily focuses on SO2 as the pollutant of interest because other pollutants (PM2.5, NO2, and Ozone) contain more "noise" with respect to identifying potential opportunistic industrial emissions during smoke events (Agarwal et al., 2023). To wit, we do not rely on PM2.5 because its concentrations are directly elevated by wildfire smoke, making it difficult to isolate the contribution of industrial sources (Borgschulte et al., 2024).[11] Further, NO_2 presents measurement challenges. Our data provide NO_2 rather than the broader NO_x category, yet NO and NO_2 rapidly cycle between each other through photochemical reactions: NO is oxidized to NO_2, while NO_2 photolyzes back to NO under sunlight. These reactions proceed on the order of minutes, and the resulting quasi-equilibrium makes it challenging to attribute observed NO_2 levels to industrial activity versus atmospheric chemistry. Moreover, a substantial share of NO_2 originates from vehicle emissions, further complicating attribution. Lastly, we restrict attention away from Ozone because industrial plants do not directly emit it; instead, it forms secondarily when NO_x and volatile organic compounds (VOCs) react under solar radiation. This photochemical dependence renders Ozone less informative for detecting short-term emission behavior by firms. By contrast, SO_2 is more directly tied to combustion at stationary industrial sources and less subject to confounding by wildfire smoke or secondary atmospheric formation. Nevertheless, in Section

[11] Although wildfire smoke contains a complex mixture of pollutants, fine particulate matter ($PM_{2.5}$) constitutes approximately 90% of its mass (https://www.climatecentral.org/climate-matters/wildfire-smoke-nationwide-health-risk-2023).

5.3, we briefly examine whether the patterns of opportunistic emissions are also evident for $PM_{2.5}$, NO_2, and Ozone.

The second dataset is plant-level information from the EPA's Toxic Release Inventory (TRI) Program. Established under the Emergency Planning and Community Right to Know Act (EPCRA), the TRI program was designed to track industrial releases of toxic chemicals that have adverse impacts on human health and the environment. The database contains self-reported annual records from facilities on the quantities of toxic chemical releases, plant locations, and associated industries.[12] We then link the TRI data with the AQS data to identify EPA monitoring stations located in proximity to industrial plants. To mitigate concerns about mechanical correlations between contemporaneous plant counts and monitor readings, we align each monitor's pollution measurements with plant counts from the preceding year. Our baseline sample comprises 460 unique SO_2 monitors observed between 2011 and 2023.[13] Figure 2 displays the geographic distribution of these monitors. The SO_2 monitors are broadly dispersed across the United States, with denser concentrations in regions characterized by higher levels of economic activity, such as California, the East North Central region, and the Mid-Atlantic.

3.3. Plant-level Thermal Infrared Radiations

[12] Under the EPCRA, reporting is mandatory for facilities that (i) operate in TRI-covered sectors, (ii) employ more than 10 full-time workers, and (iii) release any EPCRA Section 313–listed chemical above the regulatory threshold in a given year. Although TRI data are self-reported, the EPA devotes substantial resources to ensuring reporting accuracy through compliance monitoring, inspections, enforcement actions, penalties for misreporting, and systematic data verification and cross-checking. Detailed reporting requirements are provided in the EPA's TRI Threshold Screening Tool (https://www.epa.gov/toxics-release-inventory-tri-program/tri-threshold-screening-tool). Because of its nationwide coverage and detailed disclosure of direct plant-level emissions, the TRI has become a standard resource in empirical research on corporate environmental behavior and performance (e.g., Hsu et al., 2023; Li et al., 2025; Mastromonaco, 2015).

[13] According to EPA (2023), approximately 500 unique SO_2 monitors were active during the 2019–2021 period (https://www.epa.gov/system/files/documents/2022-08/SO2_2021.pdf). Our sample is smaller because we exclude monitors that did not record any wildfire smoke coverage over the study period.

We employ satellite imagery to measure plant-level thermal infrared radiation (TIR), which serves as a proxy for a plant's capacity utilization. Consistent with the second law of thermodynamics, energy transformations in production processes inevitably generate waste heat, which can be detected as TIR. Accordingly, variation in a facility's TIR provides a close approximation of its energy consumption and operational intensity. We obtain satellite-derived TIR data from NASA's Landsat 8/9 and MODIS platforms, which provide surface-level measurements at a spatial resolution of 30 meters. The imagery is processed and archived by the United States Geological Survey (USGS) and updated on an eight-day cycle, reflecting the orbital period required for Landsat satellites to achieve global coverage.[14] To extract plant-level measures, we process the TIR images using Google Earth Engine (GEE) and map each facility to its geographic coordinates. Plant-level TIR is defined as the mean TIR values within a 250 m^2 circular area centered on the facility's location.

To account for background thermal variation, we also compute TIR values for a buffer zone surrounding each facility. The buffer zone is defined as the 10 km^2 circular area around the plant, excluding the plant itself. These buffer values provide a benchmark for distinguishing production-related thermal signals from exogenous heat sources, such as wildfires, sun-heated surfaces, and traffic. Our final TIR sample covers daily-level TIR observations for 3,946 plants owned by publicly listed U.S. companies from 2020 to 2024.[15]

3.4. Descriptive Statistics

[14] Landsat 8 and 9 satellites operate in sun-synchronous orbits, with each satellite revisiting the same location on Earth every 16 days. Because their orbital cycles are internationally staggered, the two satellites together provide an effective revisit interval of eight days, allowing sequential imaging of the same facility first by Landsat 8 and then by Landsat 9 (or vice versa).

[15] We use the sample provided by a data vendor (Alt Data Tech Pty. Ltd.) to conduct the analysis. For the U.S. market, the data vendor provides TIR data only for the plants of U.S. publicly listed firms.

Table 1 presents the descriptive statistics of the main variables used in the regression analyses. The 24-hour average of SO_2 has a mean of 0.828 parts per billion, close to the number reported by the EPA (2021). The mean of D(*Wildfire Smoke*) is 0.133, suggesting that an average monitor in our sample experiences one day of wildfire smoke coverage every 7 days, or 48 days annually. There is nearly one industrial plant within a one-mile radius of a monitor. When we increase the radius of identifying industrial plants, there are mechanically more nearby industrial plants. For example, the ring-shaped area spanning 1–2 miles from a plant covers three times the space of the inner 1-mile radius.

To validate our assumption that the pollution readings by monitors located near plants capture the emissions of those plants, we assess the correlation between SO_2 readings by a monitor and the number of nearby plants surrounding the monitor. Figure 3 plots the relationship between the pollutant concentration recorded by a monitor ($PM_{2.5}$ and SO_2) and the number of nearby industrial plants. Panel (a) illustrates the results for $PM_{2.5}$. We find a much higher $PM_{2.5}$ reading on smoke days, consistent with wildfire being a major source of naturally caused $PM_{2.5}$. Further, there is a monotonic increase in a monitor's $PM_{2.5}$ readings as its nearby plant counts increase. For example, adding a plant to a monitor with zero nearby plants in its one-mile radius increases $PM_{2.5}$ reading by 35.9% (7.28 to 9.88). Similar patterns are found for SO_2 in Panel (b). There is a roughly 40% increase in SO_2 concentration when we compare monitors with one nearby plant to those with no nearby plants.[16] More interestingly, SO_2 readings appear to be more sensitive to each additional nearby plant on smoke days than on non-smoke days.

[16] Note that the SO_2 level appears lower on smoke days when the number of nearby plants is below three. This is likely due to seasonal and geographic heterogeneities in the pollutant readings, because the differences disappear when we demean the data to adjust for seasonal and area factors. In regression analyses, we confirm that SO_2 readings are significantly higher on smoke days.

Overall, the pattern in Figure 3 validates our research design of using pollution readings from monitors co-located with industrial plants to identify opportunistic pollution behavior. Meanwhile, there is preliminary evidence that SO_2 readings are more sensitive to wildfire smoke coverage when a monitor is surrounded by more industrial plants. We next turn to regression analysis for a more formal investigation.

4. Main Results

4.1. Research Design

We leverage cross-monitor distance to industrial plants to identify strategic SO_2 emissions concealed by wildfire smoke. This identification relies on the premise that industrial SO_2 emissions would be detected by nearby EPA monitors and quickly dilute as emissions drift away from their sources. As established in prior studies—and corroborated by our analysis—this premise appears to be well supported by the data. Essentially, this approach uses the SO_2 readings from monitors on non-smoke days as the benchmark level and examines deviations from this baseline on smoke days, comparing readings from monitors located near industrial plants with those farther away. Specifically, we estimate the extent of opportunistic SO_2 emissions of industrial plants during wildfire smoke days using the following regression specification:

$$\begin{aligned} SO_{2id} = {} & \beta_1 D(Wildfire\ \ Smoke)_{id} + \beta_2 D(Wildfire\ \ Smoke)_{id} \times Nearby\ Plants \\ & + \beta_3 Controls + \alpha_{iyw} + \gamma_d + \epsilon_{id} \end{aligned} \tag{1}$$

where i indexes a monitor, and d indexes a day when the SO_2 level is monitored. The observation unit is at the monitor-day level. The dependent variable (SO_2) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. $D(Wildfire\ \ Smoke)$ equals one if a monitor i is covered by wildfire smoke on day d if its coordinates are covered by a wildfire smoke plume on that day, as detected by the HMS operated by the NOAA. Nearby Plants counts the number of TRI plants within different distance ranges in the prior year.

The vector Controls includes atmospheric variables (i.e., daily average temperature and precipitation) around a given monitor to account for potential differences in weather conditions on and off wildfire smoke days.[17] We include a set of high-dimensional fixed effects: *Monitor* × *Year* × *Week* fixed effects (i.e., α_{iyw}) to absorb short-term trends in pollution level driven by unobservable shocks, e.g., short-term weather dynamics (thermal inversion, wind directions) or shifts in residential and economic activities driven by wildfire smoke. By doing so, we compare cross-sectional variations of pollutant levels among monitors within the same week. We include *Day of the Week* fixed effects (i.e., γ_d) to remove variations of pollutant levels during weekdays and weekends. Standard errors are at the monitor level to correct any serial correlation within a monitor over time.

Our primary variable of interest is *D*(*Wildfire Smoke*) × *Nearby Plants*, where *Nearby Plants* is the number of industrial plants within a certain distance from each monitor. We use distance ranges of 1 mile, 1–2 miles, 2–3 miles, and 3–5 miles to examine the effects of wildfire smoke on SO_2 levels. For example, *Nearby Plants* (*1–2 miles*) is the number of industrial plants located between 1 and 2 miles from a given monitor. We expect β_2 to be positive and diminish as the radius increases. A positive sign of β_2 would suggest that industrial plants likely strategically increase their SO_2 emissions during smoke days.

[17] In Appendix Table A3, we include additional wind-related controls, i.e., wind speed and direction. Because the wind data sourced from NOAA's National Centers for Environmental Prediction (NCEP) reanalysis covers only around half of the SO2 monitors in our baseline sample within a 50-mile radius, the sample size is much smaller. Nonetheless, we find results that are qualitatively similar to our baseline findings.

We illustrate our research design in Figure 4. In Chart (a), we plot monitors and industrial plants in Cook County, Illinois. This plot shows that monitors in different locations are exposed to vastly different levels of industrial activities. In Charts (b) to (d), we present the daily smoke volume coverage for several states in the Midwest region from June 12–15, 2023. The monitors (indicated by the red triangles) are exposed to large daily variations in exposure to wildfire smoke, which is heavily shaped by atmospheric conditions, especially the direction and speed of wind. As a result, our main variable of interest, *D*(*Wildfire Smoke*) × *Nearby Plants*, captures the difference in SO_2 concentrations between smoke days and non-smoke days for monitors near industrial zones and monitors off industrial zones.[18]

4.2. Baseline Results

Table 2 presents our baseline findings. In Column (1), we focus on the potential opportunistic behaviors of pollutant emissions by industrial plants within a one-mile radius of a monitor. Specifically, we regress the SO_2 level on the indicator of wildfire smoke *D*(*Wildfire Smoke*) and its interaction with *Nearby Plants* (*1 mile*), with other controls and fixed effects. The coefficient estimate of *D*(*Wildfire Smoke*) is 0.057 and significant at the 1% level, suggesting that wildfire smoke increases SO_2 concentration by 6.9% (0.057/0.828), or about twice the size of the SO_2 difference between weekdays and weekend days.[19] The coefficient estimate of our main variable of interest, *D*(*Wildfire Smoke*) × *Nearby Plants* (*1 mile*), is positive and significant at the 1% level. This evidence suggests that SO_2 levels are further elevated during smoke days when a monitor is co-located with industrial plants. The economic

[18] The specification follows the spirit of a difference-in-differences research design. The first difference, *D*(*Wildfire Smoke*), captures the difference in SO_2 concentrations between smoke days and non-smoke days for a given monitor. The second difference, *D*(*Wildfire Smoke*) × *Nearby Plants*, captures the relative difference in SO_2 concentrations between smoke days and non-smoke days for monitors with and without nearby industrial plants.
[19] We find that SO_2 concentrations are 0.026 units lower on weekends compared to weekdays.

effect is also meaningful. Monitors with an industrial plant located within one mile report 0.014 units higher SO2 concentration than those without such nearby plants, or 25% (0.014/0.057) of the impact of wildfire smoke. Thus, comparing SO_2 readings between smoke and non-smoke days within the same week, we find that air monitor readings in industrial areas are more sensitive to the arrival of wildfire smoke. This result provides suggestive evidence that industrial plants opportunistically release more air pollution under the cover of wildfire smoke.[20]

In Columns (2)–(3) of Table 2, we further assess how the SO_2 reading response to wildfire smoke events varies when the nearby emitting plants are located farther away. We predict that as plants are located farther away from monitors, the emitted SO_2 quickly dilutes in the air, and any opportunistic behavior would be more difficult to detect (EPA, 1992). To test this conjecture, we increase the radius around each focal monitor to identify its nearby plants by changing *Nearby Plants* (*1 mile*) to the number of industrial plants within the 3-mile and 5-mile distance bands. In Columns (2) and (3), we observe a rapidly diminishing coefficient in both magnitude and statistical significance when the nearby plants include those from within a 3- or 5-mile radius of the focal monitor, reflecting a decreasing marginal contribution of each plant on nearby monitors' readings as the two become farther apart. This highly localized pollution gap on smoke days suggests that our results cannot simply be explained by different levels of air pollutants on smoke days and non-smoke days. Instead, these findings suggest that industrial plants strategically use wildfire smoke to disguise their pollution activity and emit more pollutants during smoke days.

[20] In OA Table 1, we also find stronger results when wildfire smoke persists for more than one day, suggesting that it takes time for facilities to adjust their production or pollution control devices to fully exploit the pollution window created by wildfire smoke.

In Column (4) of Table 2, we further break down smoke coverage by severity, based on HMS classifications. We focus on how light, medium, and heavy smoke affect SO_2 emissions from nearby plants within the 3-mile radius.[21] We find that the interaction terms *D*(*Light Smoke*) × *Nearby Plants* (*3 miles*), *D*(*Medium Smoke*) × *Nearby Plants* (*3 miles*), and *D*(*Heavy Smoke*) × *Nearby Plants* (*3 miles*) are all statistically significant at the 5% level. However, we do not find significant differences across these coefficients, suggesting that plants take advantage of the presence of smoke, regardless of severity, as a strategic cover to increase emissions. This pattern reinforces the interpretation that wildfire smoke serves as a convenient opportunity to conceal polluting activity.[22]

We conduct two placebo tests to rule out the possibility that our results are driven by a spurious relation between smoke days and pollutant concentration levels across different monitors. In the first test, we maintain the annual total number of days (n) each monitor is covered by wildfire smoke and randomly assign the n days across the year. We generate 1,000 placebo samples and re-estimate the corresponding coefficient of *D*(*Placebo Smoke*) × *Nearby Plants* (*1 mile*) based on each placebo sample. Chart (a) of Figure 6 plots the distribution of the pseudo coefficient estimates for the interaction term. Overall, the coefficient estimates based on the placebo samples are normally distributed and centered on the mean of 0. Furthermore, the actual estimate from Column (1) of Table 2 lies far to the right of the entire distribution of estimates from these placebo samples. In the second test, we scramble the number of nearby plants (*Nearby Plants* (*1 mile*)) across all monitors in a given year while maintaining the cross-sectional distribution of this variable. Analysis based on

[21] Focusing on plants within a 3-mile radius ensures that: (i) we have a reasonable level of variations in the number of nearby plants across monitor–severity combinations, and (ii) pollution from a nearby industrial facility can make a meaningful impact on nearby monitors' readings.
[22] Heavy smoke days are rare in our sample, accounting for only 0.79% of smoke days.

1,000 simulations obtains a similar finding as the first test: the actual estimate from Column (1) of Table 2 lies well above the entire distribution of the pseudo estimates in Chart (b). Together, the placebo tests underscore the strength of our main finding by confirming that it is highly unlikely to be driven by chance.

4.3. The Role of Plant Operating Capacity

We conduct several tests to tie the temporary increase in SO_2 near plants on wildfire smoke days to their opportunistic emission behavior and, more specifically, their capacity utilization. In the first test, we use plant-level thermal radiation data to assess changes in daily plant-level operating capacity around wildfire smoke coverage. Most of the production activities in plants consume energy and simultaneously emit thermal infrared radiation (TIR). Recent studies show that changes in TIR help reflect adjustments in operational activities and forecast future firm performance (Xue et al., 2025). Thus, if plants temporarily escalate their capacity to emit more pollution during wildfire smoke days, we should observe a contemporaneous increase in their TIR.

Following Xue et al. (2025), we overlay plants' coordinates from the EPA with TIR data from NASA's satellites, which generate high-resolution thermal infrared sensing at a resolution of 30 meters. Because the satellites capture both production-generated TIR as well as non-productional TIR (e.g., wildfire, natural heat), we compute the adjusted plant TIR, *DTIR*, as the difference between the observed factory TIR and the surrounding base-level natural TIR.[23] The natural TIR is measured as the TIR of the circular area centered around the plant, excluding the plant itself. To further purge common trends in TIR across plants, we

[23] In addition to controlling for the "background" thermal infrared radiation (TIR) around a given plant, we also verify in the data that none of the plants in the sample are located within an active burn zone of wildfire, meaning that the smoke is drifted from wildfire sources located elsewhere. Thus, any uptick in *DTIR* of a plant during wildfire smoke days cannot be attributed to heat generated by wildfires per se.

compute another measure, *MDTIR*, which is the difference between a plant's *DTIR* and the average *DTIR* among all the other plants on a given day. Figure 5 illustrates our use of daily *DTIR* as a proxy for plant capacity utilization to capture the strategic capacity utilization during wildfire smoke days. The example plant, a Procter & Gamble (P&G) facility in Mehoopany, PA, is outlined in yellow at the center. Two concentric circles mark the core factory area (0.25 km^2, radius = 282 m) and the surrounding buffer zone (10 km^2, radius = 1.78 km). Chart (a) shows TIR of the P&G facility on April 1, 2023 (a day without wildfire smoke coverage); Chart (b) shows TIR of the P&G facility on May 27, 2023 (a day with wildfire smoke coverage). We visualize *DTIR* using a blue-to-red scale, with red indicating higher plant capacity utilization. We find that the *DTIR* of the P&G facility appears much redder on the smoke day than on the non-smoke day, providing preliminary evidence of increased plant capacity utilization during smoke exposure. To formally test this strategic plant capacity utilization, we then perform the following regression using plant-level daily TIR data:

$$Adjusted\ TIR_{jd} = \beta_1 D(Wildfire\ Smoke)_{jd} + \beta_3 Controls + \alpha_{jyq} + \gamma_d + \epsilon_{jd} \qquad (2)$$

where $Adjusted\ TIR_{jd}$ is either *DTIR* or *MTIR* for plant *j* on day *d,* and $D(Wildfire\ Smoke)_{jd}$ indicates whether plant *j* is under the coverage of wildfire smoke on day *d*. The regression controls for weather conditions (i.e., temperature and precipitation) around the plant and fixed effects, including *Plant* × *Year* × *Quarter (Plant* × *Year* × *Month)* and *Day of the Week* fixed effects.[24] The high-dimensional fixed effects structure helps absorb seasonal trends in TIR or plant production that may also correlate with the occurrence of wildfire smoke. The

[24] A typical plant is scanned by satellites once every week. Thus, the plant-level regression cannot accommodate *Plant* × *Year* × *Week* fixed effects.

coefficient of interest, β_1, captures the difference in plant TIR between days with wildfire smoke and the rest of the days.

Table 3 presents the results. In Column (1), when we control for weather conditions, *Plant* × *Year* × *Quarter* fixed effects, and day-of-the-week fixed effects, the estimation shows that the adjusted thermal infrared radiation is about 0.233 units higher on days when a given plant is under wildfire smoke coverage, or 18.3% of the sample median of *DTIR*. Similar results are obtained in Column (2) when the outcome variable is *MTIR*, the market-adjusted TIR. In Columns (3) and (4), we further tighten the regressions by replacing Plant × Year × Quarter fixed effects with *Plant* × *Year* × *Month* fixed effects. The estimation shows that the positive association between wildfire smoke coverage and plant TIR is robust to controlling for seasonality at the monthly level. For instance, in Column (3), we find that the plant's adjusted TIR is 0.222 units higher when it is under wildfire smoke coverage. Inference for *MTIR* remains similar in Column (4).

In our second test, we separate the sample into workdays and non-workdays. Non-workdays include weekends and federal holidays. Because most workers are on Monday-to-Friday shifts and weekend shifts often operate at partial capacity, this operating schedule limits plants' ability to increase pollution by ramping up production capacity or turning off end-of-pipe waste management devices. Consequently, we expect the opportunistic behavior of industrial plants to diminish on non-workdays. Panel (a) of Table 4 presents the results of this cross-sectional analysis. While we continue to observe an elevated SO_2 during smoke days in both subsamples, the coefficient estimate of *D*(*Wildfire Smoke*) × *Nearby Plants* is significant only in the workday subsample, i.e., Column (1).

In the third test, we compare the effects of wildfire smoke on the strategic pollution activities of industrial plants between industries with high production flexibility and industries with low production flexibility. Plants operating in different industries often differ in their ability to adjust production capacity. Certain industries (e.g., power plants, oil refineries, and steel plants) usually feature continuous operations because shutting down and restarting equipment is costly. In contrast, other industries often operate with partial capacity and can flexibly scale up or scale down their production to take advantage of favorable conditions. We expect that plants from the latter category will exhibit stronger opportunistic responses to the pollution opportunity created by wildfire smoke.

To investigate this possibility, we build on the findings of Zou (2021) to identify a number of industries that are most likely to engage in opportunistic pollution. According to Zou (2021), plants from the following industries react most positively to the pollution window created by the scheduled shutdown of nearby EPA monitors: oil and gas extraction (NAICS 211), mining (NAICS 212), wood product manufacturing (NAICS 321), printing and related support activities (NAICS 323), primary metal manufacturing (NAICS 331), fabricated metals manufacturing (NAICS 332), truck transportation (NAICS 484), and waste management (NAICS 562). We then separate plants in these "suspicious" industries from the rest of the plants and examine the heterogeneity of our findings. Plants in "suspicious" industries, industries with more flexible production capacity, account for just one-third of nearby plants. Nonetheless, the results in Panel (b) of Table 4 show that the pollution response to wildfire smoke is nearly three to four times stronger when a monitor's nearby plants operate in an industry with more flexible production capacity.

In Appendix Table A2, we conduct a further corroborating analysis by isolating monitors with nearby power plants. Unlike plants operating in "suspicious" industries outlined above, power plants usually run at stable capacity utilization for cost-efficiency concerns. For example, a report by the National Renewable Energy Laboratory (2012) suggests that frequent capacity adjustment by power plants leads to large thermal and pressure stresses, which cause fatigue damage to plant components and increase maintenance costs. Thus, if the abnormal pollution spike near industrial plants on smoke days is driven by their opportunistic adjustment of capacity utilization, we expect this phenomenon to be less obvious when air monitors are tracking power plants' pollution. We obtain the location of 1,709 power plants from the EPA's Clean Air Markets Program Data and compute the number of nearby power plants for each EPA monitor. Results reported in Appendix Table A2 are consistent with our conjecture: the abnormal pollution spike is much weaker when monitors are picking up power plants' pollution.

Overall, the results in this subsection provide more concrete evidence linking the increased production activities of industrial plants near EPA monitors to the higher SO_2 readings.

4.4. The Role of Financial Constraint

In this subsection, we examine the role of financial constraints in shaping plants' strategic emission behaviors. Firms facing tighter financial constraints have stronger incentives to save on abatement costs and therefore emit more pollution during wildfire smoke periods. Because plant-level financial constraints cannot be measured directly, we proxy for them at the industry level.[25] Specifically, we use machine learning-based financial constraints

[25] As not all industrial plants in EPA dataset belong to publicly listed firms. It is not possible to measure financial constraint for those plants at the parent-firm level. In the spirit of Yonker (2017), we use the financial constraint level

developed by Linn and Weagley (2024) and calculate the industry-average level of financial constraints. Plants operating in industries with above-median levels of financial constraints are classified as financially constrained. We expect opportunistic behavior to be more pronounced among these plants.

Table 5 presents the heterogeneous effects by financial constraint status. In Panel (a), we use the equity-focused constraint measure. In Column (1), we find that the coefficient estimate of *D*(*Wildfire Smoke*) × *Nearby Plants-FinConE* (*1 mile*) is significant at the 1% level, with an effect size (0.028) about twice that of our baseline estimates. In Column (2), however, the effect is muted for plants operating in industries that are less financially constrained. In Columns (3) and (4), we use the debt-focused constraint measure from Linn and Weagley (2024) and find quantitatively similar results. As a robustness check, we use the industry stock return to measure the financial constraint status of plants. Specifically, we label a three-digit SIC code industry in distress if its stock return (median firm-level return) is below the sample median among all industries in a year. The results in OA Table 2 remain qualitatively similar.[26] Taken together, the analyses based on industry-level proxies for financial distress provide supportive evidence that economic pressure drives the opportunistic pollution behavior of plants.

5. Additional Analyses

5.1. Environmental Enforcement

at the industry level to proxy for the financial constraint level for industrial plants.

[26] We also find that plants owned by publicly listed parent firms exhibit stronger strategic emission behavior. Public firms face greater pressure to meet short-term financial and market performance targets, which enhance their incentives to cut pollution abatement costs during wildfire smoke periods (Thomas et al. 2022). Results in OA Table 3 confirm this notion, consistent with the view that capital market scrutiny and quarterly performance pressures amplify opportunistic environmental behavior (Shive and Forster 2020).

In this subsection, we explore whether the effect of wildfire smoke on the strategic polluting activities of industrial plants is attenuated when environmental enforcement is stronger. We first examine county-level nonattainment status in relation to the EPA's environmental regulation. A county that fails to meet the National Ambient Air Quality Standards for one or more air pollutants is classified as a nonattainment area. Plants located in nonattainment areas face stricter regulations and pressure to bring local pollution levels below regulatory thresholds. As a result, plants in nonattainment counties should have a much weaker incentive to exploit wildfire smoke to disguise their emissions because the resulting increase in pollution readings could prolong their nonattainment status. We obtain the annual attainment status from the EPA Green Book and re-estimate the baseline model using the subsamples of attainment and nonattainment counties.[27]

Panel A of Table 6 presents the results. We first note that the correlation between the presence of wildfire smoke and SO_2 concentration is approximately twice as strong in the subsample of nonattainment counties, as evidenced by the difference in coefficient estimates of *D*(*Wildfire Smoke*) between Columns (1) and (2). This result likely indicates that air pollution caused by wildfire smoke aggravates the risk of a county being designated as nonattainment by the EPA.[28] More importantly, we find the coefficient of *D*(*Wildfire Smoke*) × *Nearby Plants* is larger in attainment counties than in nonattainment counties. For example, the effect of nearby plant counts (one-mile radius) on SO_2 is approximately four times stronger in attainment counties compared to nonattainment counties (0.020 vs. 0.005). This result

[27] In this test, we classify a county as being in attainment when the attainment status of a county is missing. However, our results are robust to including only counties with available attainment status.
[28] Consistent with this conjecture, a group of counties has tried to request local EPA agencies to remove wildfire smoke days from regulatory records, arguing that the high pollution levels during such days are the result of "exceptional events" and should not be used to assess local compliance with air quality standards. For more details, see: https://www.muckrock.com/news/archives/2023/may/23/ wildfire-smoke-exceptional-event/.

suggests that the risk of prolonging nonattainment status may suppress local plants' opportunistic pollution behavior.

Next, we explore how the pollution gap on smoke days varies with local monitoring frequency. Using satellite data, Zou (2021) finds that areas with once-every-six-day monitoring schedules have significantly worse air quality during unmonitored days, suggesting that industrial plants increase pollution when the likelihood of detection is lower. Since such an intermittent monitoring schedule primarily occurs among PM detection monitors, we identify SO_2 monitors that co-locate with intermittent PM monitors in the same monitoring sites and study whether the pollution response to wildfire events differs near such SO_2 monitors.[29] Essentially, we use the operating frequency of PM monitors as a proxy for the overall intensity of air pollution monitoring, as particulate matter is usually emitted alongside other pollutants during production processes such as fuel combustion and material processing.

In Panel B of Table 6, we parse the sample based on monitoring frequency and find that the coefficient of *D*(*Wildfire Smoke*) × *Nearby Plants* is greater when monitors work every day or one out of three days than when the monitors work once every six days. Importantly, these findings do not imply that more frequent monitoring encourages opportunistic behavior. Rather, this pattern suggests that when monitors operate less frequently, the incentive for plants to exploit wildfire smoke as a cover for excess emissions diminishes since they already face minimal regulatory oversight. In other words, it is precisely

[29] According to the EPA, each monitoring site can host multiple monitoring devices (i.e., monitors) that track different ambient air pollutants.

because of heightened scrutiny that industrial plants may resort to subtler means, such as leveraging wildfire smoke, to circumvent environmental regulations.[30]

5.2. Role of Local Socioeconomic Conditions

We further examine whether plants' opportunistic pollution under the cover of wildfire smoke is related to local socioeconomic conditions. To this end, we look at county-level residential attitudes toward climate change, obtained from the Yale Program on Climate Change Communication (Marlon et al., 2022; Howe et al., 2015). Specifically, we obtain the estimated percentage of local residents who "think corporations should do more to address global warming." In areas with greater consensus that corporations should internalize their externalities related to climate change, we expect weaker corporate responses to the pollution opportunity during wildfire smoke. In addition, we also focus on several local socioeconomic factors at the census tract level: poverty, unemployment, population density, education, and minority population. By splitting the main sample into subsamples using the sample medians of the six variables, we explore the heterogeneous response of firms' strategic SO_2 emissions.

Results are presented in Table 7. In Columns (1) and (2), the estimations show that the SO_2 pollution spike during wildfire smoke is nearly three times stronger in counties with a weaker emphasis on corporations' role in addressing climate change (Coef. 0.025 versus 0.008). This finding suggests that local stakeholders' pro-environmental beliefs (e.g., employees, customers, communities) effectively curbs local facilities opportunistic pollution. In terms of other local socioeconomic factors, we find a greater SO_2 spike on days with wildfire smoke in regions with higher poverty ratios, higher unemployment rates, and low population density (Panel (a)). Such areas might host more plants with an incentive to exploit the pollution window provided by wildfire smoke. Alternatively, local residents may be more receptive to trading off lower air quality for cost savings brought to the local factories. In

[30] In an untabulated test, we examine whether the presence of local newspapers serves as a potential disciplining mechanism. There appears to be no strong evidence that local newspapers reduce facilities' opportunistic pollution, perhaps because of the difficulty in detecting such a behavior and linking it to specific facilities.

either case, these heterogeneities appear to be generally consistent with the literature examining the spatial correlation between pollution exposure and local income level (Banzhaf et al., 2019). In contrast, we do not find that local total population, educational attainment, or ethnic composition matter.

5.3. Alternative Pollutants

In the main tests, we focus on SO_2 because it is the most direct industrial pollutant (compared to NO_2, NO, etc.). In a robustness test, we also explore the effect of wildfire smoke on industrial plants' emissions of other air pollutants. Table 8 shows that our main results hold for other pollutants, including NO_2, Ozone, and $PM_{2.5}$. In terms of economic significance, we find that NO_2 emissions are most responsive to wildfire smoke. Compared to monitors with no industrial plant, monitors with one nearby industrial plant within 1 mile detect 27% (0.109/0.400) more NO_2 on smoke days. On the other hand, monitors with one nearby industrial plant within 1 mile detect only 1.9% (0.033/1.761) more $PM_{2.5}$.

5.4. Robustness Tests

In this section, we further subject our main results to alternative specifications with different fixed effects structures. Table 9 presents the results using alternative specifications of our main model. We first experiment with coarser fixed effects in Columns (1) and (2). Specifically, we replace *Monitor* × *Year* × *Week* fixed effects in the baseline model with either *Monitor* × *Year* × *Month* or *Monitor* × *Year* × *Quarter* fixed effects. Thus, instead of comparing SO_2 readings across smoke and non-smoke days within the same week, we now perform the comparison within the same month or quarter. Furthermore, in Columns (3) to (5), we include fixed effects for each specific date during the sample period to absorb common trends across all monitors, and we pair these fixed effects with monitor-by-time fixed effects. Overall, our results remain robust to a wide range of different specifications, and the coefficient estimates are similar to those in Table 2.

6. Conclusion

Leveraging wildfire smoke releases as an exogenous deterioration in air quality, we examine the strategic timing of industrial pollution under the cover of wildfire smoke. When we compare EPA monitors with and without nearby plants, we find that monitors with more nearby plants record a greater increase in air pollutants during days with wildfire smoke. Analyses based on plant-level thermal infrared radiation, workdays versus non-workdays comparison, and variations in plant capacity utilization suggest that the additional increase in pollution is driven by a temporary uptick in industrial plants' capacity utilization. We further find suggestive evidence that wildfire-induced pollution complicates environmental regulation. On the one hand, the opportunistic pollution increase is more evident in areas with more regulatory slack, i.e., counties that are in attainment of the EPA's environmental laws. On the other hand, this behavior is also more pronounced among plants under greater surveillance by the EPA, i.e., plants near EPA monitors that function at a higher monitoring frequency. Areas with lower socioeconomic status host disproportionately more plants with opportunistic pollution behavior. Overall, our paper highlights a new source of environmental externality caused by wildfire events: businesses' strategic pollution emission actions hidden under the haze.

Our paper contributes to the literature on firms' opportunistic behaviors, environmental regulation evasion, and the broader impacts of climate change on toxic emission practices in the private sector. While existing research often focuses on financial manipulations and cost-saving strategies, our findings highlight that firms also exploit external environmental shocks to temporarily evade pollution monitoring through the strategic timing of toxic emissions. By linking climate-driven events with industrial emission strategies, our paper also demonstrates how worsening wildfire conditions caused by climate change can create a negative externality by inadvertently incentivizing firms to increase pollution under the cover of haze. Our evidence is relevant to the policy discussion on corporate responses to environmental challenges and strategies for curbing firms' strategic air pollution behaviors.

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Figure 1: County-level exposure to wildfire smoke

This figure illustrates counties' exposure to wildfire smoke in the contiguous United States. Chart A shows the annual average number of days with wildfire smoke experienced by U.S. counties from 2011 to 2023. Chart B presents the geographic distribution of wildfire smoke during the same period. The values represent the time-series average number of smoky days per year for each county.

Chart A: County annual days with wildfire smoke

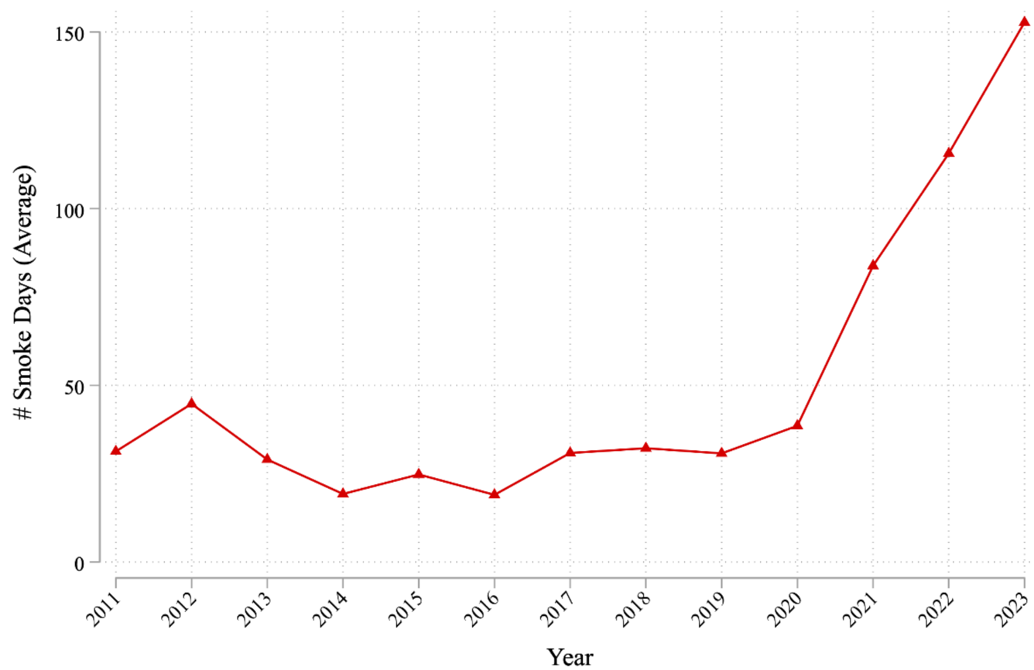


Chart B: Geographic distribution of wildfire smoke

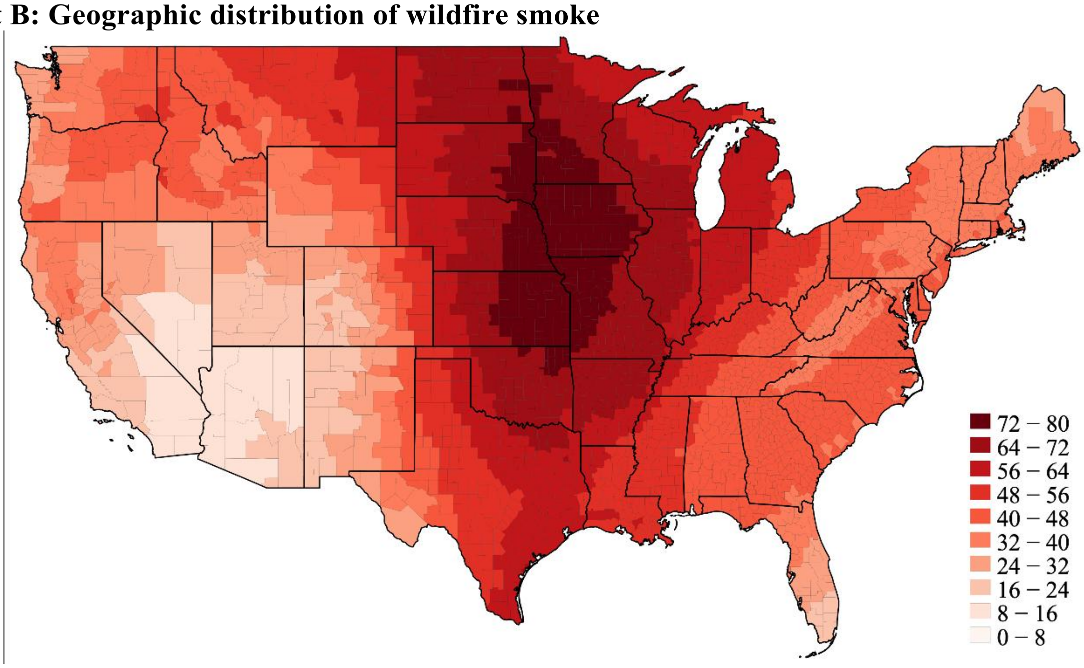


Figure 2: The distribution of EPA monitors

This figure presents the distribution of EPA outdoor monitors for sulfur dioxide (SO_2) across the United States. Each red triangle (▲) represents a single SO_2 monitor. The sample period spans from 2011 to 2023.

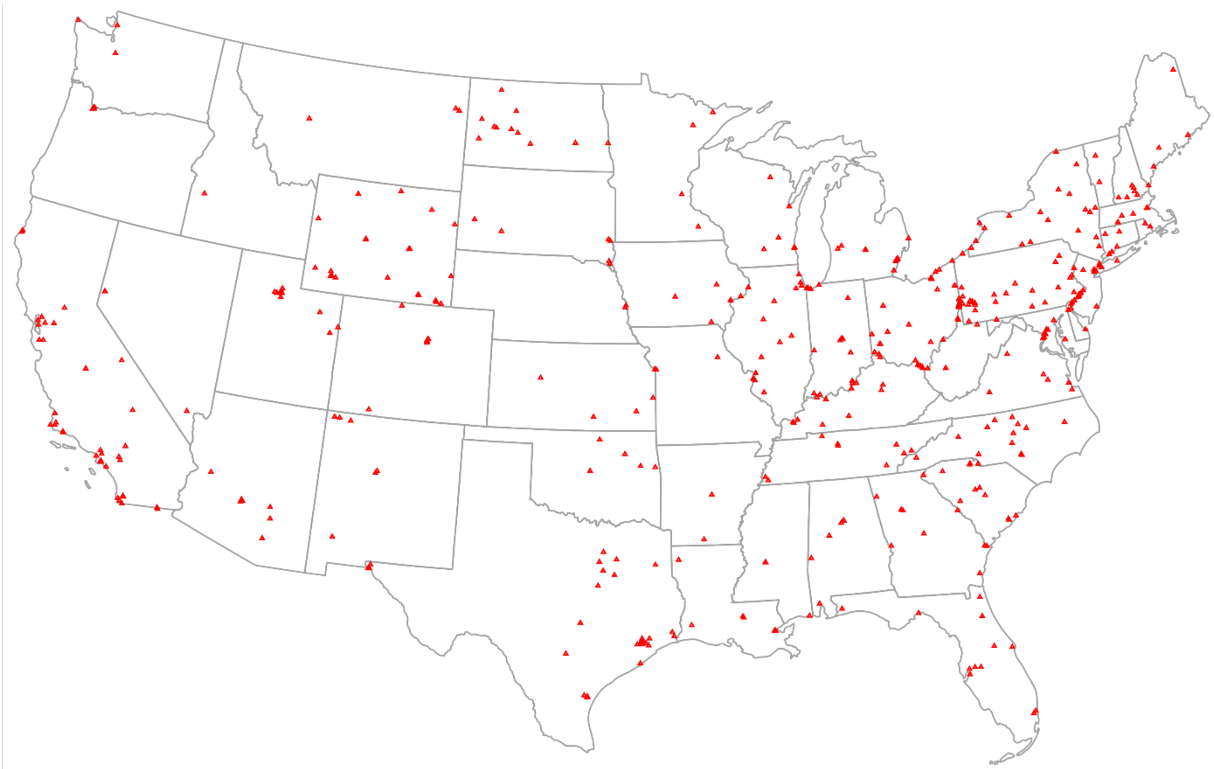
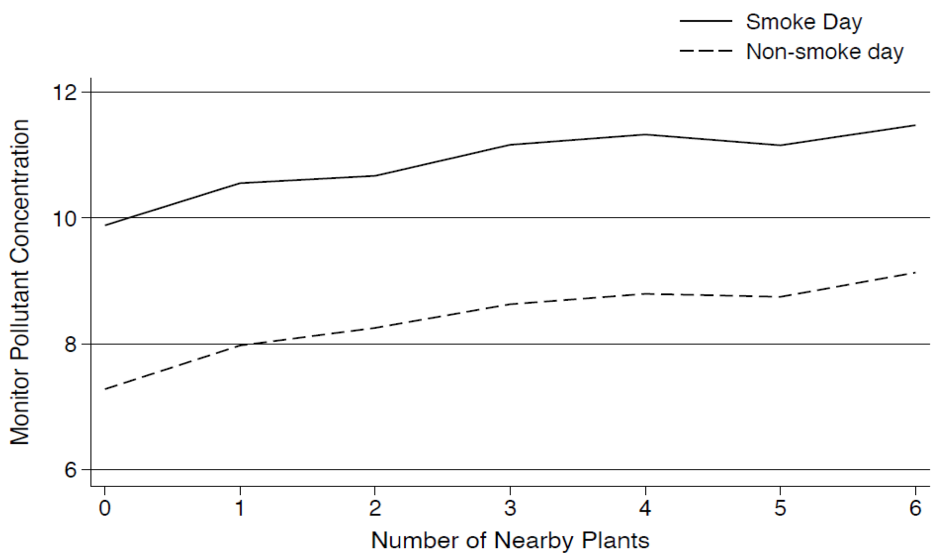


Figure 3: Nearby plants around monitors and pollution level

This figure plots the relationship between pollutant concentration recorded by a monitor and the number of nearby plants. In each chart, the x-axis represents the number of nearby plants, and the y-axis represents the annual average of daily pollutant concentration for $PM_{2.5}$ (Chart (a)) and SO_2 (Chart (b)). The plots are generated separately for non-smoke days (dashed lines) and smoke days (solid lines).

(a) $PM_{2.5}$



(b) SO_2

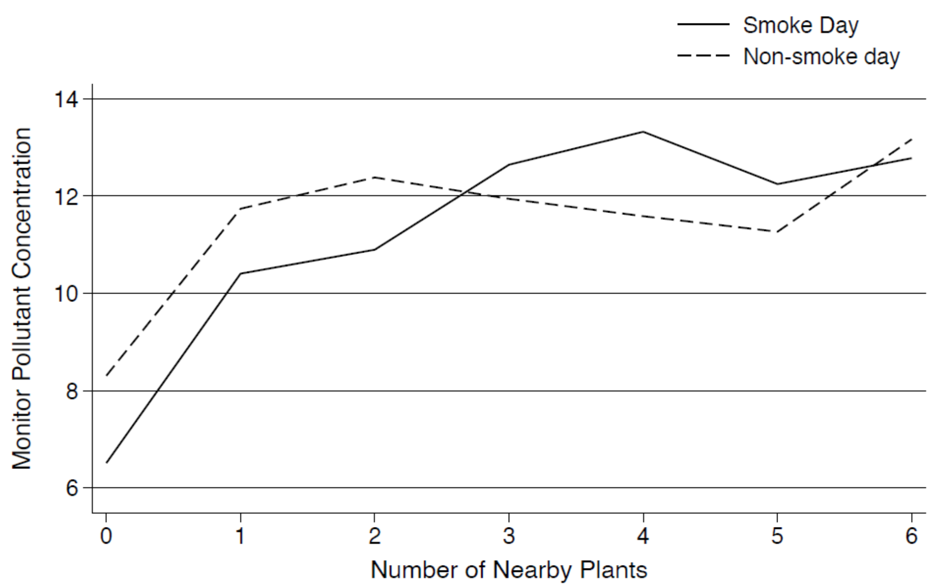


Figure 4: Illustration of monitors' exposure to plants and wildfire smoke

This figure illustrates our empirical approach using the EPA monitors in Cook County, Illinois. Chart (a) maps the proximity of industrial plants to EPA monitors, with three concentric circles—at 1-mile and 3-mile radius—surrounding each monitor. The red triangles (▲) indicate EPA outdoor monitors, while the blue diamonds (◆) indicate TRI plants. Charts (b) through (d) show the daily smoke coverage for several states in the Midwest U.S. from June 13–15, 2023. The gray shading (■) represents smoke presence based on satellite images from NOAA's HMS. The blue area highlights Cook County in Illinois.

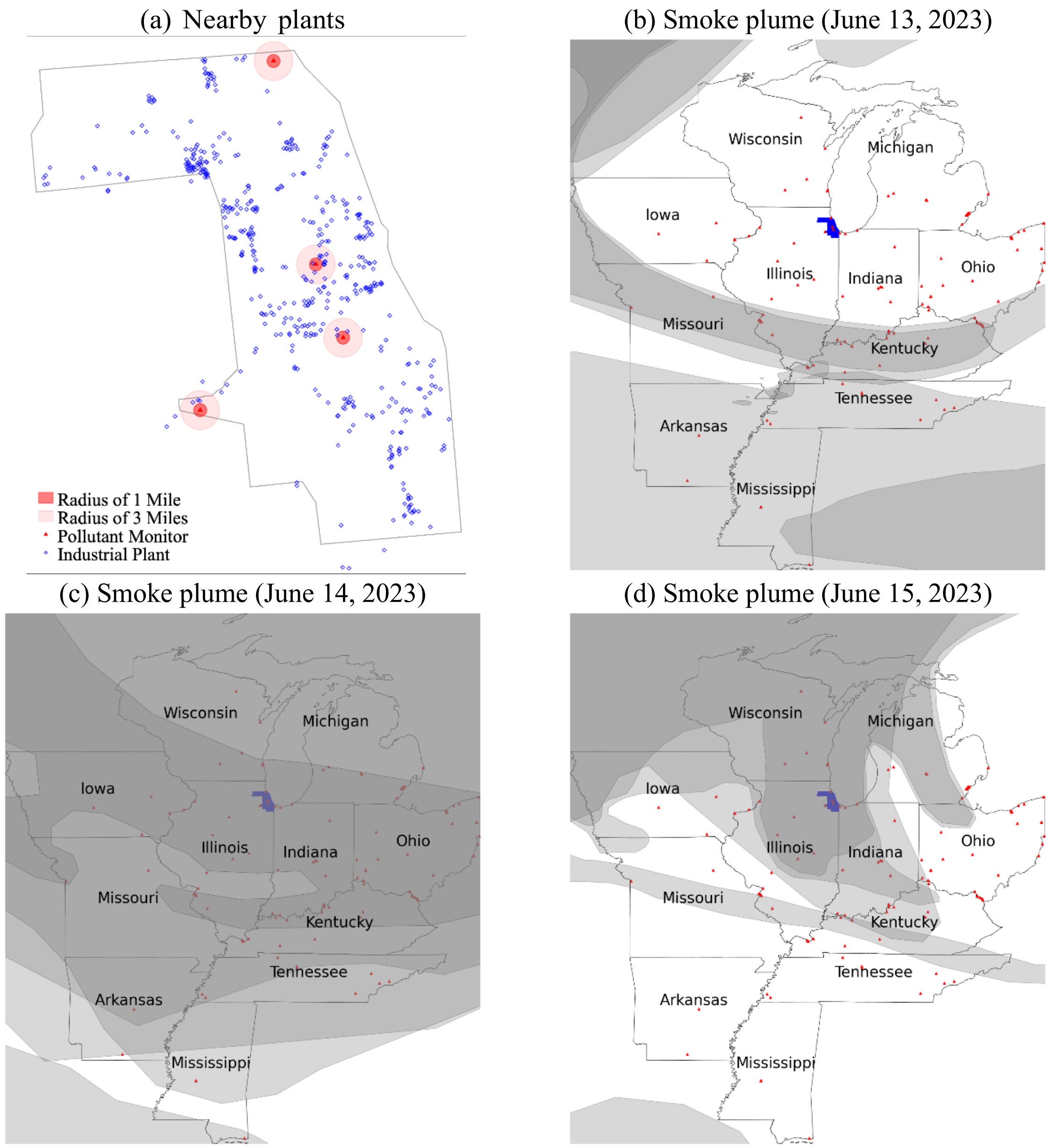


Figure 5: Measuring plant-level thermal infrared radiation

This figure illustrates how we use satellite-based imagery to measure plant daily thermal infrared radiation (TIR), a proxy for capacity utilization. The illustrated plant belongs to Procter and Gamble Co. (Mehoopany, PA (41.573441'N, 76.04696°W)), which sits in the center of the images and is outlined by a yellow-dashed regular polygon. There are two concentric circles. The smaller circle captures the core factory area centered at the plant coordinates (area = 0.25 km^2, radius = 282 meters). The larger circle represents the "buffer zone" (area = 10 km^2, radius = 1.78 km). Chart (a) shows the area's TIR on April 1, 2023, a day without wildfire smoke. Chart (b) shows the area's TIR on May 27, 2023, a day with wildfire smoke. TIRRaw represents the TIR value of the small circular area, i.e., the core factory area. TIRBare represents the average TIR value of the larger circle (excluding the inner circle), i.e., the buffer zone. The eventual measure of plant-level adjusted TIR, DTIR, is computed as TIRRaw - TIRBare.

(a) Non-smoke day (Apr 1, 2023) (b) Smoke day (May 27, 2023)

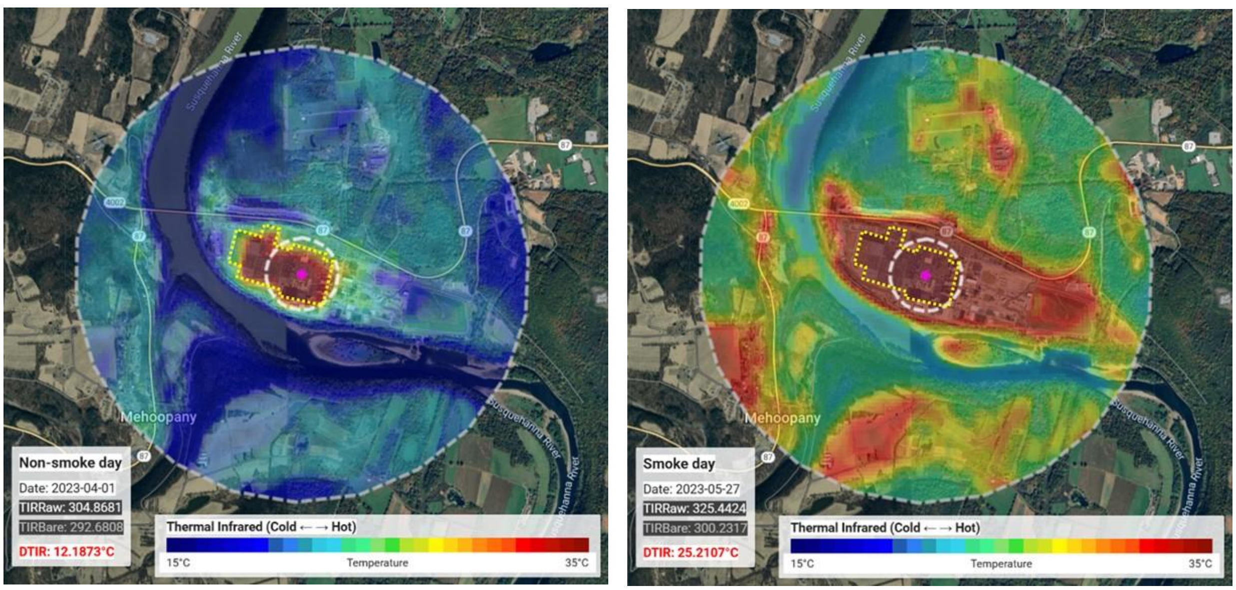
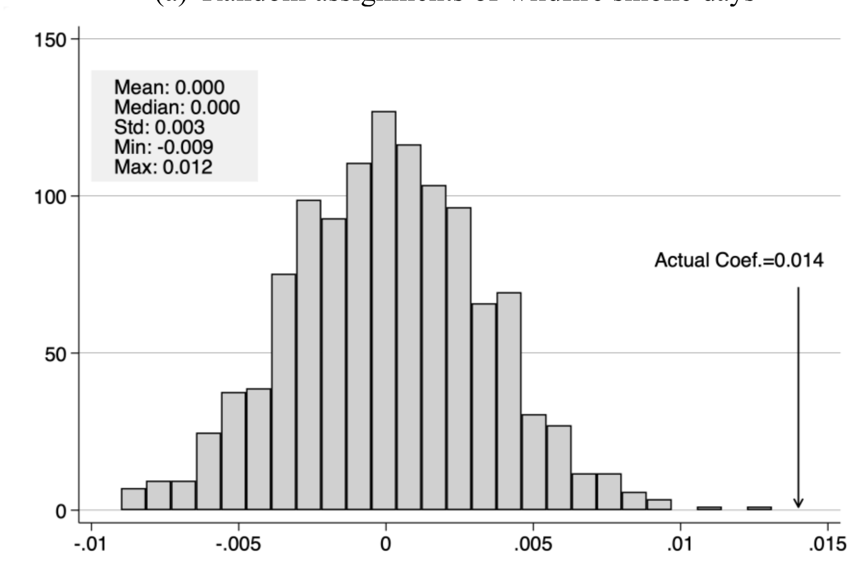


Figure 6: Placebo tests

This figure shows the distribution of the coefficient estimates for *D*(*Wildfire Smoke*) × *Nearby Plants* (*1 mile*) by re-estimating the baseline model with placebo samples. In Chart (a), we retain the annual number of smoke days (n) for each monitor and randomly assign the n days across the entire calendar year. In Chart (b), we scramble the number of nearby plants (*Nearby Plants* (*1 mile*)) across all monitors in a given year while maintaining the actual distribution of this variable. In both charts, we generate 1,000 placebo samples and record the corresponding coefficient *for D*(*Wildfire Smoke*) × *Nearby Plants* (*1 mile*) based on each sample. The "Actual Coef.=0.014" refers to the coefficient estimate for *D*(*Wildfire Smoke*) × *Nearby Plants* (1 *mile*) from Column (1) of Table 2.

(a) Random assignments of wildfire smoke days



(b) Random assignments of nearby plant counts

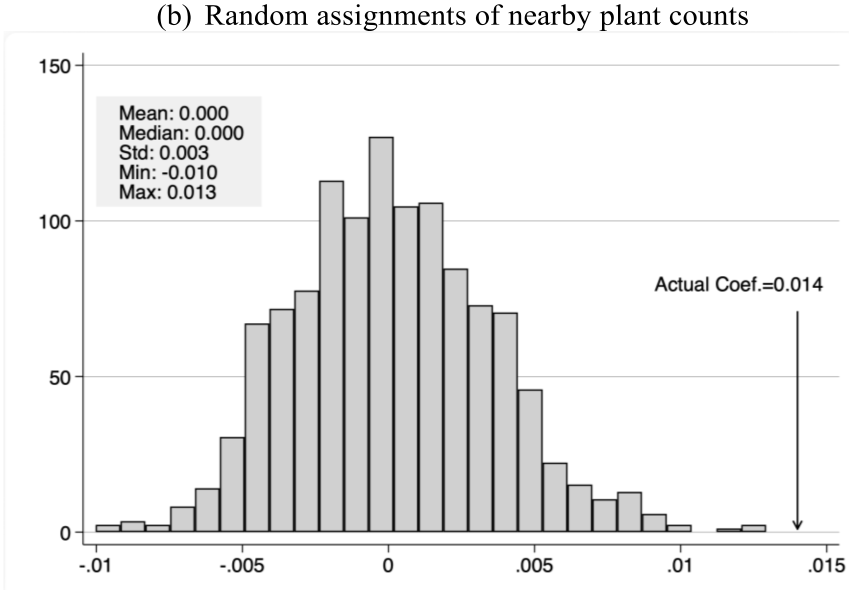


Table 1: Summary statistics

This table reports the summary statistics for the key variables used in the analyses. Appendix Table A1 includes the variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles.

	Obs.	**mean**	**p25**	**p50**	**p75**	**SD**
SO_2	1,458,971	0.828	0.087	0.413	1.030	1.308
D(Wildfire Smoke)	1,458,971	0.133	0.000	0.000	0.000	0.339
D(Light Smoke)	1,458,971	0.101	0.000	0.000	0.000	0.302
D(Medium Smoke)	1,458,971	0.024	0.000	0.000	0.000	0.152
D(Heavy Smoke)	1,458,971	0.008	0.000	0.000	0.000	0.089
Nearby Plants (1 mile)	1,458,971	0.945	0.000	0.000	1.000	1.521
Nearby Plants (3 miles)	1,458,971	5.475	1.000	3.000	8.000	6.306
Nearby Plants (5 miles)	1,458,971	11.518	2	8	16	14.484
Nearby Plants-High Flexibility (1 mile)	1,458,971	0.340	0.000	0.000	0.000	0.726
Non-workday	1,458,971	0.310	0.000	0.000	1.000	0.463
1-in-6 Monitor	982,897	0.205	0.000	0.000	0.333	0.345
Nonattainment	961,098	0.653	0.000	1.000	1.000	0.476
Population	1,178,199	3457.552	2334.000	3243.250	4412.000	1605.458
Population Density	1,178,199	3047.280	153.740	1327.755	3612.807	6197.761
Poverty Rate	1,164,654	0.224	0.107	0.189	0.320	0.148
Low Education	1,164,654	0.102	0.055	0.089	0.138	0.064
Unemployment Rate	1,164,654	0.041	0.024	0.037	0.054	0.025
Minority Residents	1,164,654	0.388	0.110	0.300	0.637	0.309
NO_2	2,035,674	8.051	2.758	5.958	11.381	7.031
Ozone	5,219,824	0.032	0.024	0.032	0.040	0.011
$PM_{2.5}$	3,172,697	7.899	4.400	6.700	10.100	5.161
DTIR	414,491	1.757	0.058	1.275	3.112	2.768
MDTIR	414,491	1.757	0.383	1.352	2.812	2.182

Table 2: Do plants emit more pollution during days with wildfire smoke?

This table reports the regression results on whether plants emit more air pollution during days with wildfire smoke. The dependent variable (*SO_2*) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. *D*(*Wildfire Smoke*) indicates monitor–days covered by wildfire smoke plumes as detected by the Hazard Mapping System operated by the National Oceanic and Atmospheric Administration. *Nearby Plants* counts the number of TRI plants within different distance ranges from a given monitor. For example, *Nearby Plants* (*1 mile*) is the number of plants located within one mile of a given monitor. Temperature and Precipitation measure the ground temperature and rainfall, respectively, in the area surrounding a monitor. All columns include Monitor × Year × Week fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	SO_2			
	(1)	(2)	(3)	(4)
Radius =	*<= 1mile*	*<=3 miles*	*<=5 miles*	*<=3 miles*
D(Wildfire Smoke) × Nearby Plants	0.014***	0.004***	0.001***	
	(0.004)	(0.001)	(0.000)	
D(Light Smoke) × Nearby Plants				0.004***
				(0.001)
D(Medium Smoke) × Nearby Plants				0.005***
				(0.002)
D(Heavy Smoke) × Nearby Plants				0.003**
				(0.002)
D(Wildfire Smoke)	0.057***	0.047***	0.054***	
	(0.006)	(0.007)	(0.007)	
D(Light Smoke)				0.047***
				(0.007)
D(Medium Smoke)				0.049***
				(0.009)
D(Heavy Smoke)				0.069***
				(0.010)
Temperature	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation	-0.091***	-0.091***	-0.091***	-0.091***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	1458971	1458971	1458971	1458971
Adjusted R^2	0.626	0.626	0.626	0.626
Monitor × Year × Week FE	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes

Table 3: Evidence from plant thermal infrared radiation

This table reports the regression results related to changes in plant-level thermal infrared radiation around wildfire smoke coverage. The sample consists of plant-by-day thermal infrared radiation data generated by remote satellite sensing between 2020 and 2024. The dependent variable, *DTIR*, is the difference in thermal infrared radiation between a given plant and its surrounding bare lands (a circular area of 10 km^2, excluding the plant itself). *MTIR* is the difference between a plant's *DTIR* and the same-day average *DTIR* across all other plants. Columns (1) and (2) include Plant × Year × Quarter fixed effects and Day of the Week fixed effects. Columns (3) and (4) include Plant × Year × Month fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	DTIR (1)	MTIR (2)	DTIR (3)	MTIR (4)
D(Wildfire)	0.233***	0.196***	0.222***	0.203***
	(0.030)	(0.025)	(0.018)	(0.018)
Temperature	0.039***	0.040***	0.042***	0.043***
	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation	-0.135***	-0.104***	-0.136***	-0.104***
	(0.007)	(0.006)	(0.007)	(0.005)
Constant	1.139***	1.126***	1.092***	1.073***
	(0.010)	(0.009)	(0.013)	(0.012)
Observations	414491	414491	411218	411218
Adjusted R^2	0.602	0.574	0.704	0.658
Plant × Year × Quarter FE	Yes	Yes	No	No
Plant × Year × Month FE	No	No	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes

Table 4: The role of changes in industrial production intensity

This table reports the results of regressions examining whether the greater increase in pollution during smoke days recorded by monitors with more nearby plants is driven by these plants' strategic increase in production activities. In Column (1) of Panel (a), the sample includes workday observations. In Column (2), the sample includes non-workday observations, i.e., weekends and other public holidays. In Panel (b), we distinguish plants with greater flexibility to ramp up their production to take advantage of the emission window during wildfire smoke days. The industries with high flexibility are identified based on the findings in Zou (2021). They include oil and gas extraction (NAICS 211), mining (NAICS 212), wood product manufacturing (NAICS 321), primary metal manufacturing (NAICS 331), fabricated metals manufacturing (NAICS 332), truck transportation (NAICS 484), and waste management (NAICS 562). Nearby Plants-High Flexibility (1 mile) counts the number of plants operating in one of these industries within a 1 mile from a given monitor. The dependent variable (SO_2) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. All columns include Monitor × Year × Week fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Panel (a): Pollution response during workdays versus non-workdays

Dependent Variable	SO_2	
	Workday	Non-Workday
	(1)	(2)
D(Wildfire Smoke) × Nearby Plants (1 mile)	0.019***	0.007
	(0.005)	(0.006)
D(Wildfire Smoke)	0.057***	0.047***
	(0.007)	(0.008)
Temperature	-0.010***	-0.011***
	(0.001)	(0.001)
Precipitation	-0.092***	-0.067***
	(0.006)	(0.006)
Coef. of (1)−(2) (*p*-value)	0.013 (0.059)	
Observations	1005908	450528
Adjusted R^2	0.631	0.667
Monitor × Year × Week FE	Yes	Yes
Day of the Week FE	Yes	Yes

Panel (b): Distinguishing plants with flexible production capacity

Dependent Variable	SO_2	
	(1)	(2)
D(Wildfire Smoke) × Nearby Plants-High Flexibility (1 mile)	0.038***	
	(0.008)	
D(Wildfire Smoke) × Nearby Plants-Low Flexibility (1 mile)		0.012*
		(0.007)
D(Wildfire Smoke)	0.058***	0.063***
	(0.007)	(0.006)
Temperature	-0.008***	-0.008***
	(0.001)	(0.001)
Precipitation	-0.091***	-0.091***
	(0.006)	(0.006)
Coef. of (1) − (2) (p-value)	0.026 (0.007)	
Observations	1458971	1458971
Adjusted R^2	0.626	0.626
Monitor × Year × Week FE	Yes	Yes
Day of the Week FE	Yes	Yes

Table 5: Financially constrained industry

This table reports the heterogeneity of the baseline results in relation to financial constraints. We use machine learning-based financial constraint measures developed by Linn and Weagley (2024) and calculate the industry-average level of financial constraints. In columns (1) and (2), we use equity-focused constraints. In (3) and (4), we use debt-focused constraints. The dependent variable (SO_2) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. The row "Coef. Diff (*p*-value)" denotes the difference in the estimated coefficient and the *p*-values for the interaction terms between either Columns (1) and (2) or (3) and (4). All columns include Monitor × Year × Week fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	SO_2			
	(1)	(2)	(3)	(4)
D(Wildfire Smoke)	0.028***			
× Nearby Plants-FinConE (1 mile)	(0.008)			
D(Wildfire Smoke)		0.010		
× Nearby Plants-NonFinConE (1 mile)		(0.007)		
D(Wildfire Smoke)			0.028***	
× Nearby Plants-FinConD (1 mile)			(0.008)	
D(Wildfire Smoke)				0.009
× Nearby Plants-NonFinConD (1 mile)				(0.007)
D(Wildfire Smoke)	0.059***	0.065***	0.060***	0.066***
	(0.006)	(0.007)	(0.006)	(0.006)
Temperature	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation	-0.091***	-0.091***	-0.091***	-0.091***
	(0.006)	(0.006)	(0.006)	(0.006)
Coeff. Diff (*p*-value)	0.019 (0.045)		0.019 (0.036)	
Observations	1458971	1458971	1458971	1458971
Adjusted R^2	0.626	0.626	0.626	0.626
Monitor × Year × Week FE	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes

Table 6: Does environmental monitoring curb opportunistic pollution?

This table reports the heterogeneity of the baseline results in relation to the air quality monitoring intensity in local counties. Columns (1) and (2) focus on attainment status with respect to the National Ambient Air Quality Standards. Columns (3) and (4) focus on the scheduled monitoring frequency of monitors near industrial sites. In Column (1), the subsample includes monitors in attainment counties. In Column (2), the subsample includes monitors in nonattainment counties regarding major monitored pollutants. In Column (3), the subsample includes observations from SO_2 monitors co-located with PM monitors that function every day or one out of three days. In Column (4), the subsample includes those SO_2 monitors that co-locate with PM monitors that turn on once every six days. The dependent variable (SO_2) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. All columns include Monitor × Year × Week fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	SO_2			
	Attainment	Nonattainment	1/1 in 3	1 in 6
	(1)	(2)	(1)	(2)
D(Wildfire Smoke) × Nearby Plants (1 mile)	0.020*	0.005	0.019***	0.010*
	(0.010)	(0.004)	(0.005)	(0.005)
D(Wildfire Smoke)	0.044***	0.084***	0.058***	0.060***
	(0.006)	(0.012)	(0.008)	(0.015)
Temperature	-0.007***	-0.010***	-0.007***	-0.008***
	(0.001)	(0.002)	(0.001)	(0.002)
Precipitation	-0.070***	-0.119***	-0.097***	-0.111***
	(0.005)	(0.010)	(0.009)	(0.012)
Coeff. of (1) − (2) (p-value)	0.015 (0.094)		0.009 (0.118)	
Observations	831707	865110	865110	306846
Adjusted R^2	0.636	0.628	0.628	0.602
Monitor × Year × Week FE	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes

Table 7: The role of local socioeconomic factors

This table reports the cross-sectional heterogeneity of our baseline finding in relation to local socioeconomic conditions. For each of the six local variables, we split the sample into high and low groups by the median value. The dependent variable (*SO_2*) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. All columns include Monitor × Year × Week fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Panel (a): Partitioning by poverty, unemployment, and population density

Dependent Variable	SO_2					
	Climate Change Attitude		Poverty		Unemployment	
	Strong	Weak	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
D(Wildfire Smoke)	0.008	0.025***	0.018***	0.005	0.018***	0.006
× Nearby Plants (1 mile)	(0.006)	(0.008)	(0.006)	(0.006)	(0.007)	(0.005)
D(Wildfire Smoke)	0.062***	0.050***	0.051***	0.067***	0.069***	0.052***
	(0.010)	(0.007)	(0.008)	(0.009)	(0.010)	(0.006)
Temperature	-0.010***	-0.006***	-0.008***	-0.009***	-0.010***	-0.007***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
Precipitation	-0.093***	-0.089***	-0.099***	-0.084***	-0.113***	-0.066***
	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)	(0.006)
Coeff. Diff. (*p*-value)	0.017 (0.040)		0.014 (0.052)		0.012 (0.081)	
Observations	800679	642700	642660	521994	646602	518052
Adjusted R^2	0.619	0.628	0.612	0.656	0.61	0.658
Monitor × Year × Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel (b): Partitioning by population, education, and ethnicity

Dependent Variable	SO_2					
	Pop Density		Education		Minority	
	High	Low	High	Low	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
D(Wildfire Smoke)	0.012**	0.021**	0.014**	0.016**	0.015***	0.017*
× Nearby Plants (1 mile)	(0.006)	(0.011)	(0.006)	(0.007)	(0.006)	(0.009)
D(Wildfire Smoke)	0.063***	0.053***	0.061***	0.056***	0.051***	0.065***
	(0.009)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
Temperature	-0.011***	-0.006***	-0.010***	-0.007***	-0.009***	-0.008***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Precipitation	-0.104***	-0.074***	-0.101***	-0.082***	-0.089***	-0.096***
	(0.009)	(0.008)	(0.007)	(0.010)	(0.007)	(0.010)

(*Continued*)

Table 7—*Continued*

Coeff. Diff. (p-value)	-0.009 (0.216)		-0.003 (0.390)		-0.003 (0.407)	
Observations	468940	709259	636350	528304	622578	542076
Adjusted R^2	0.627	0.625	0.613	0.653	0.617	0.641
Monitor × Year × Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Additional EPA-monitored air pollutants

This table reports the robustness of our findings to alternative air pollutants. In Column (1), the outcome variable is the daily concentration of nitrogen dioxide (NO_2, in parts per billion) recorded by EPA monitors. In Column (2), the outcome variable is daily Ozone concentration (parts per million). In Column (3), the outcome variable is the daily $PM_{2.5}$ concentration (micrograms per cubic meter). All columns include Monitor × Year × Week fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	NO_2	Ozone	$PM_{2.5}$
	(1)	(2)	(3)
D(Wildfire Smoke) × Nearby Plants (1 mile)	0.109***	0.015***	0.033**
	(0.023)	(0.003)	(0.015)
D(Wildfire Smoke)	0.400***	0.262***	1.761***
	(0.025)	(0.003)	(0.020)
Temperature	-0.139***	0.007***	0.053***
	(0.007)	(0.001)	(0.003)
Precipitation	-0.758***	-0.120***	-0.950***
	(0.026)	(0.002)	(0.012)
Observations	1844294	4957230	2839084
Adjusted R^2	0.757	0.653	0.525
Monitor × Year × Week FE	Yes	Yes	Yes
Day of the Week FE	Yes	Yes	Yes

Table 9: Alternative specifications

This table reports the robustness of our findings to alternative specifications. In Column (1), the regression includes Monitor × Year × Month fixed effects and Day of the Week fixed effects. In Column (2), we replace the fixed effects with Monitor × Year × Quarter fixed effects and Day of the Week fixed effects. In Column (3), we include Monitor × Year × Week fixed effects and Date fixed effects. In Column (4), we include Monitor × Year × Month fixed effects and Date fixed effects. In Column (5), we include Monitor × Year × Quarter fixed effects and Date fixed effects. The dependent variable (SO_2) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	SO_2				
	(1)	(2)	(3)	(4)	(5)
D(Wildfire Smoke) × Nearby Plants (1 mile)	0.015***	0.015***	0.012***	0.014***	0.013**
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)
D(Wildfire Smoke)	0.065***	0.073***	0.051***	0.059***	0.063***
	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Temperature	-0.005***	-0.006***	-0.006***	-0.003**	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation	-0.099***	-0.100***	-0.073***	-0.079***	-0.080***
	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)
Observations	1459481	1459499	1458971	1459481	1459499
Adjusted R^2	0.568	0.512	0.635	0.580	0.528
Monitor × Year × Week FE	No	No	Yes	No	No
Monitor × Year × Month FE	Yes	No	No	Yes	No
Monitor × Year × Quarter FE	No	Yes	No	No	Yes
Day of the Week FE	Yes	Yes	No	No	No
Date FE	No	No	Yes	Yes	Yes

Appendix

Table A1: Variable definitions

Variables	Definitions
D(Wildfire Smoke)	An indicator variable that equals one if the daily wildfire smoke plume covers a monitor's location, and zero otherwise. The daily wildfire smoke plume data is obtained from the Hazard Mapping System. [Source: HMS and EPA]
D(Light Smoke)	An indicator variable that equals one if the wildfire smoke plume covering a plant is classified by HMS as light smoke, and zero otherwise. [Source: HMS and EPA]
D(Medium Smoke)	An indicator variable that equals one if the daily wildfire smoke plume covering a plant is classified by HMS as medium smoke, and zero otherwise. [Source: HMS and EPA]
D(Heavy Smoke)	An indicator variable that equals one if the daily wildfire smoke plume covering a plant is classified by HMS as heavy smoke, and zero otherwise. [Source: HMS and EPA]
Nearby Plants	The number of industrial plants that report to the Toxic Release Inventory (TRI) within 1 mile, 3 miles, and 5 miles surrounding the EPA monitor. [Source: EPA]
Temperature	The average daily temperature at a monitor's location. [Source: PRISM]
Precipitation	The aggregated daily precipitation at a monitor's location. [Source: PRISM]
DTIR	Difference in thermal infrared radiation between the plant area (area = 0.25 km^2, radius = 282 meters) and the surrounding buffer zone (area = 10 km^2, radius = 1.78 km). Both areas are centered on the plant coordinates obtained from the EPA. [Source: EPA, NASA].
MDTIR	Difference between plant DTIR and market-wide average DTIR. [Source: NASA].
Nearby Plants-High Flexibility	Plants counted in Nearby Plants that operate in the following three-digit NAIC industries: 211, 212, 321, 323, 331, 332, 484, and 562. [Source: EPA]
Nearby Plants-FinConE	Plants counted in Nearby Plants that operate in financially distressed industries based on the equity-focused constraints developed by Linn and Weagley (2024). [Source: EPA]
Nearby Plants-FinConD	Plants counted in Nearby Plants that operate in financially distressed industries based on the debt-focused constraints developed by Linn and Weagley (2024). [Source: EPA]
Non-workday	An indicator that equals one if a day on which the pollution level is available is a weekend or holiday, and zero otherwise.
1in 6 Monitor	An indicator for EPA monitors that operate once every six days. [Source: EPA].
Nonattainment	An indicator for counties that are in violation of EPA air quality standards for major pollutants. [Source: EPA].
Climate Change Attitude	The estimated fraction of county-level residents who think corporations should do more to address global warming. [Source: Yale Program on Climate Change Communication]

Poverty Rate	The percentage of the population in poverty (measured as 100% of the federal poverty level before 2020, and 150% of the federal poverty level on and after 2020) in the census tract where a monitor is located. [Source: Social Vulnerability Index]
Population Density	The population density, measured as the total population divided by the tract area in square miles, in the census tract where a monitor is located. [Source: Social Vulnerability Index]
Low Education	The total number of residents (age 25+) without a high school diploma divided by the total number of residents in the census tract where a monitor is located. [Source: Social Vulnerability Index]
Unemployment Rate	The total number of unemployed residents (age 16+) divided by the total number of residents in the census tract where a monitor is located. [Source: Social Vulnerability Index]
Minority Residents	The total number of non-white residents divided by the total number of residents in the census tract where a monitor is located. [Source: Social Vulnerability Index]
SO_2	Sulfur dioxide concentration in the air measured in parts per billion. [Source: EPA].
NO_2	Nitrogen dioxide concentration in the air measured in parts per billion. [Source: EPA].
$PM_{2.5}$	Particulate matter (2.5) concentration in the air measured in micrograms per cubic meter. [Source: EPA].
Ozone	Ozone concentration in the air measured in parts per billion. [Source: EPA].

Table A2: Separating EPA monitors with nearby power plants

This table reports the regression results on how power plants nearby EPA monitors affect the abnormally high pollution spike on smoke days. The subsample in Column (1) includes EPA monitors without nearby power plants within a five-mile radius. In Column (2), the subsample includes monitors with at least one power plant within a five-mile radius. Fixed effects included in the regressions are denoted at the bottom of the table. Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	SO_2	
	Power Plants: No	Power Plants: Yes
	(1)	(2)
D(Wildfire Smoke) × Nearby Plants (1 mile)	0.019**	0.006
	(0.009)	(0.006)
D(Wildfire Smoke)	0.048***	0.076***
	(0.005)	(0.015)
Temperature	-0.006***	-0.012***
	(0.001)	(0.002)
Precipitation	-0.069***	-0.116***
	(0.005)	(0.011)
Observations	802572	656399
Adjusted R^2	0.674	0.582
Monitor × Year × Week FE	Yes	Yes
Day of the Week FE	Yes	Yes

Table A3: Additional controls

This table contains the results from regressions that control for wind characteristics from NOAA's National Centers for Environmental Prediction (NCEP) reanalysis: *Wind Speed* and *Wind Direction*. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	SO_2
	(1)
D(Wildfire Smoke) × Nearby Plants (1 mile)	0.014**
	(0.006)
D(Wildfire Smoke)	0.061***
	(0.010)
Temperature	-0.008***
	(0.001)
Precipitation	-0.089***
	(0.008)
Wind Speed	-0.011***
	(0.003)
Wind Direction	0.008
	(0.009)
Observations	746012
Adjusted R^2	0.635
Monitor × Year × Week FE	Yes
Day of the Week FE	Yes

Online Appendix

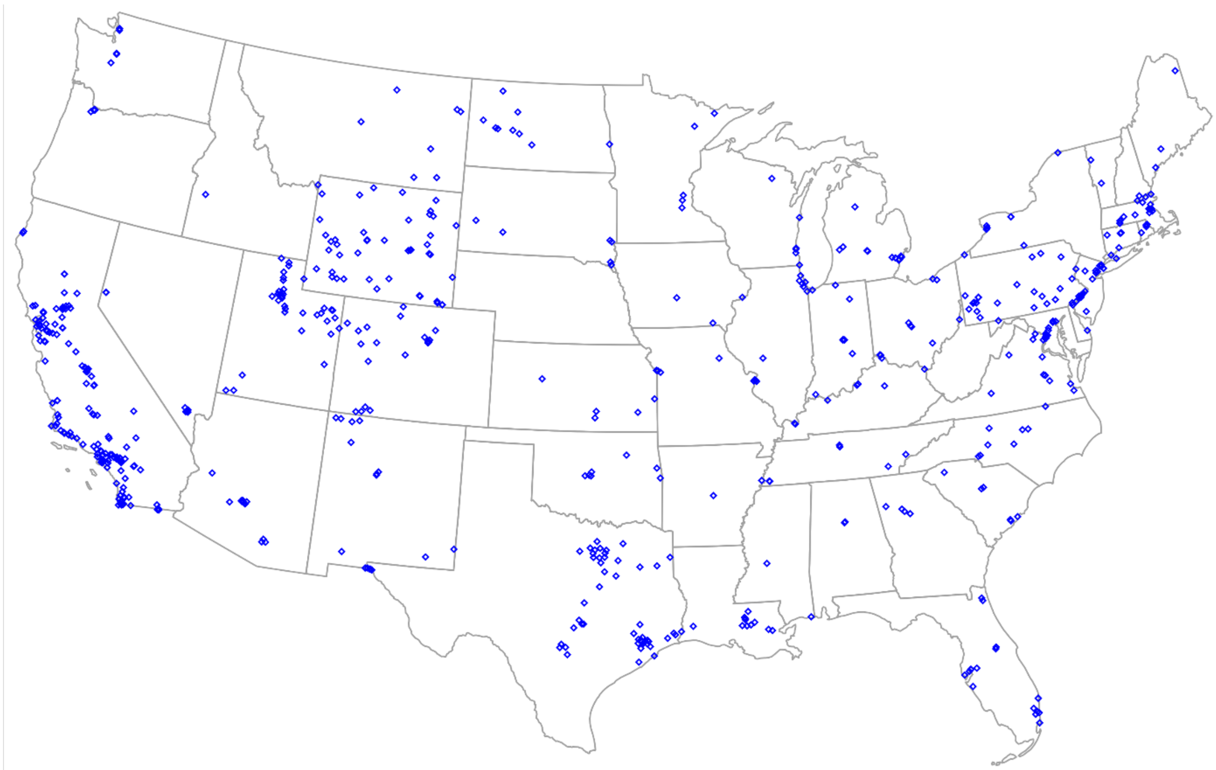
For

What Lies Beneath the Haze? Wildfire Smoke and Industrial Pollution

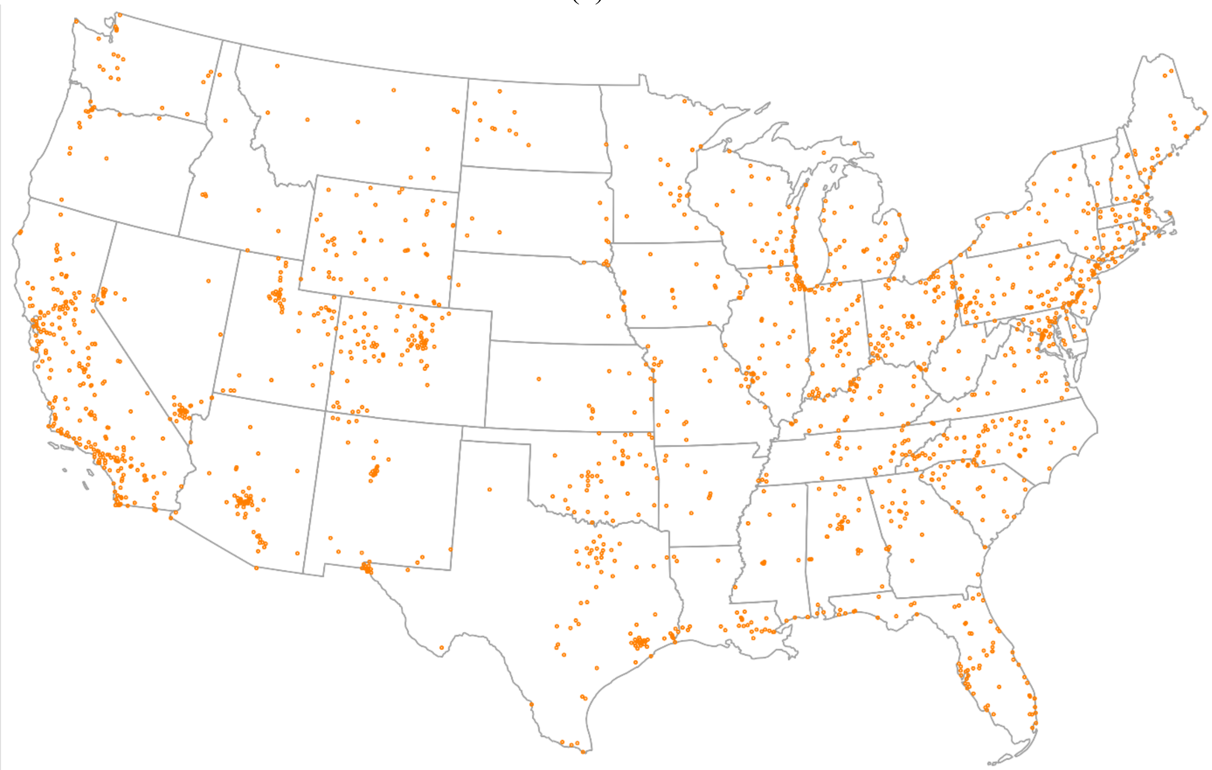
OA Figure 1: The distribution of other EPA monitors

This figure presents the distribution of EPA outdoor monitors for three primary criteria pollutants: nitrogen dioxide (NO_2), Ozone, and particles less than 2.5 micrometers in diameter ($PM_{2.5}$). The sample period spans from 2011 to 2023.

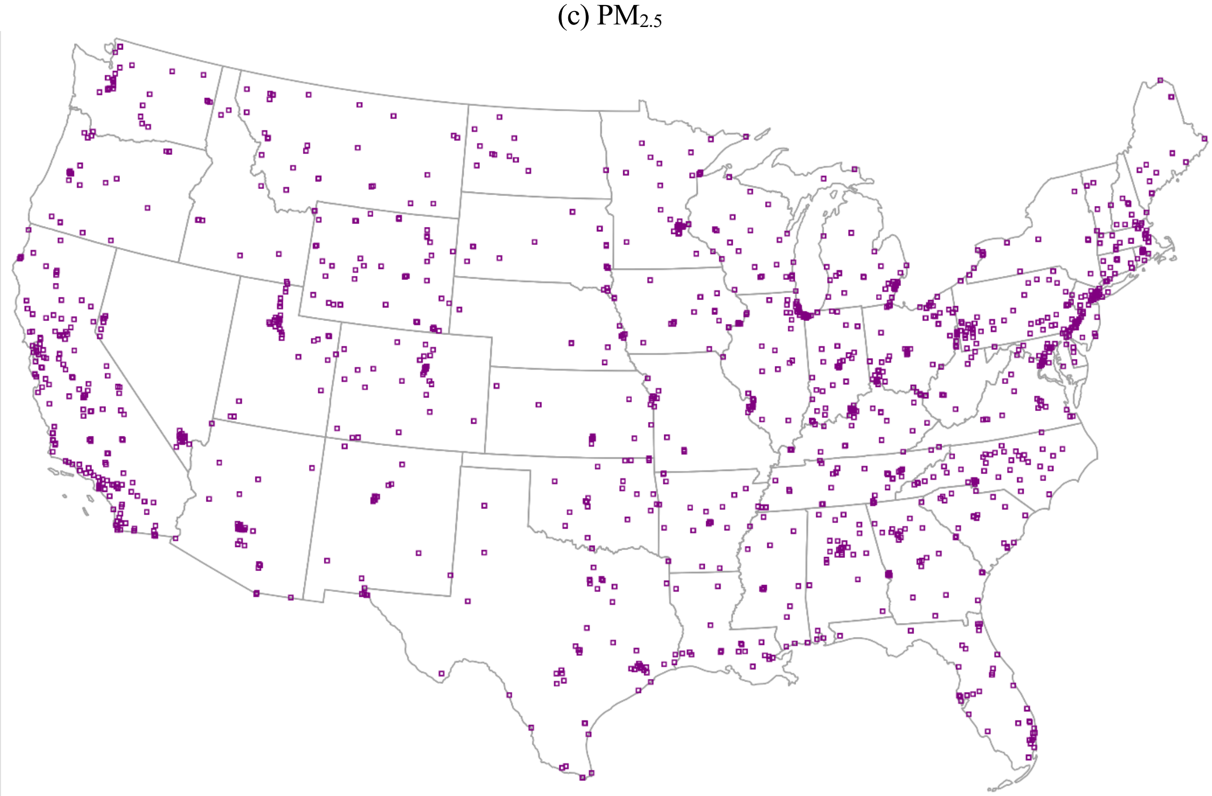
(a) NO_2



(b) Ozone

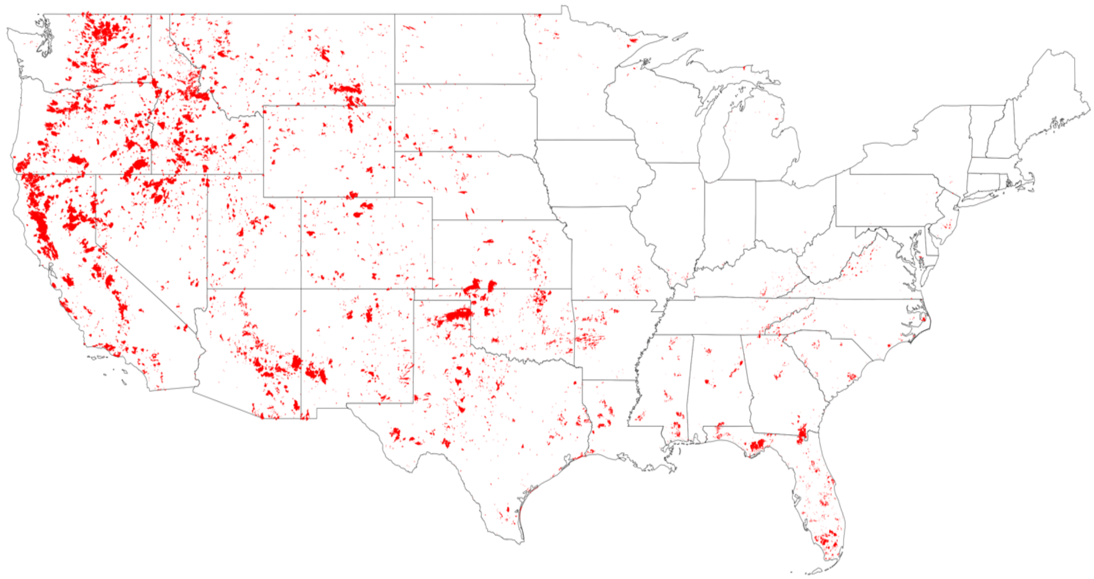


(c) $PM_{2.5}$



OA Figure 2: The distribution of wildfires

This figure plots all wildfires and the burned areas in the contiguous U.S. during 2011 and 2023.



OA Table 1: The duration of wildfire smoke

This table reports heterogeneity in the baseline results by wildfire smoke duration. The dependent variable (*SO_2*) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. *D*(*First Smoke Day*) indicates wildfire events that last one day and the first day of wildfire smoke events that span multiple days. *D*(*Subsequent Smoke Days*) flags subsequent days for wildfire smoke events that span multiple consecutive days. All columns include Monitor × Year × Week fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	SO2 (1)
D(First Smoke Day) × Nearby Plants (1 mile)	0.011***
	(0.004)
D(Subsequent Smoke Days) × Nearby Plants (1 mile)	0.017***
	(0.006)
D(First Smoke Day)	0.053***
	(0.006)
D(Subsequent Smoke Days)	0.063***
	(0.008)
Temperature	-0.008***
	(0.001)
Precipitation	-0.091***
	(0.006)
Coeff. Diff. (D(Subsequent Smoke Days) × Nearby Plants (1 mile) – D(First Smoke Day) × Nearby Plants (1 mile))	0.006
	(0.06)
Observations	1458971
Adjusted R^2	0.626
Monitor × Year × Week FE	Yes
Day of the Week FE	Yes

OA Table 2: Financially constrained industry based on stock return

This table reports the heterogeneity of the baseline results in relation to industry distress. Industry distress is measured based on the median stock return of public firms in an industry. The dependent variable (SO_2) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. All columns include Monitor × Year × Week fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	SO_2	
	(1)	(2)
D(Wildfire Smoke) × Nearby Plants-FinConR (1 mile)	0.023***	
	(0.008)	
D(Wildfire Smoke) × Nearby Plants-NonFinConR (1 mile)		0.015**
		(0.006)
D(Wildfire Smoke)	0.064***	0.061***
	(0.006)	(0.006)
Temperature	-0.008***	-0.008***
	(0.001)	(0.001)
Precipitation	-0.091***	-0.091***
	(0.006)	(0.006)
Observations	1458971	1458971
Adjusted R^2	0.626	0.626
Monitor × Year × Week FE	Yes	Yes
Day of the Week FE	Yes	Yes

OA Table 3: Public versus non-public plants

This table reports the heterogeneity of the baseline results in relation to public firm status. The dependent variable (*SO_2*) measures the level of sulfur dioxide concentration recorded by air monitoring devices installed by the EPA. All columns include Monitor × Year × Week fixed effects and Day of the Week fixed effects. Appendix Table A1 includes other variable definitions. Standard errors in parentheses underneath coefficients are clustered at the monitor level. Superscripts ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.

Dependent Variable	SO_2	
	(1)	(2)
D(Wildfire Smoke) × Nearby Plants-Public (1 mile)	0.027^{***}	
	(0.010)	
D(Wildfire Smoke) × Nearby Plants-Nonpublic (1 mile)		0.013^{***}
		(0.005)
D(Wildfire Smoke)	0.064^{***}	0.062^{***}
	(0.006)	(0.006)
Temperature	-0.009^{***}	-0.009^{***}
	(0.001)	(0.001)
Precipitation	-0.094^{***}	-0.094^{***}
	(0.006)	(0.006)
Observations	1360829	1360829
Adjusted R^2	0.623	0.623
Monitor × Year × Week FE	Yes	Yes
Day of the Week FE	Yes	Yes