Wildfires, Pollution, and Pregnancy Outcomes: Evidence from Lightning Strikes

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Abstract

Although the risk of wildfire is increasing, its impact on pollution and health is understudied due to economic confounders. Using lightning strikes as an instrumental variable, this study finds that a 1 km^2 increase in wildfire emits many pollutants well above the national air quality standards at the county average. Accordingly, the same increase in wildfires reduces birth weight by 21.2 grams and decreases gestational age by 0.1 weeks. Given the increasing number of lightning strikes due to global warming, the reduced-form effect calls for more attention to natural pollution rather than man-made pollution.

JEL Classification: Q53, Q54, I12, J13

Keywords: Wildfires, Air Pollution, Pregnancy Outcomes, Climate Change

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1 Introduction

Air pollution is a global environmental issue. Economic burdens, such as traffic and industrial emissions, are traditionally believed to be the primary sources of air pollution. Accordingly, many economic studies investigate the health effects of pollution from these sources (e.g., Currie and Walker, 2011; Currie et al., 2015; Knittel et al., 2016; Alexander and Schwandt, 2022). Thus, public policies regulate air pollution from these sources, resulting in the gradual improvement of air quality.

However, wildfires pose a new challenge to air pollution. Climate change increases fire fuel aridity and creates a more favorable fire environment (Abatzoglou and Williams, 2016). Between 2003 and 2018, approximately 1.3 million wildfires occurred in the US, burning approximately 0.4 million km^2 (Short, 2021). Wildfires then contribute to approximately 25% of the total $PM_{2.5}$ emissions in the US (Burke et al., 2021). Consequently, the concentration of $PM_{2.5}$ is elevated in wildfire-prone areas, although it is decreased over most of the US (McClure and Jaffe, 2018). The objective of this study is to investigate the impact of wildfires on air pollution and health.

Estimating the causal effects of wildfire is difficult due to the endogeneity of wildfire. For example, open burning, a form of wildfire, may be associated with agricultural income, which may improve health status.[1] Another concern is the crime rate, which may be associated with arson. Many wildfires are cased by arson which may occur in areas with high crime rates. The neighborhood disorder may discourage exercise outside and increase mental stress, which may affect health outcomes.

To overcome the challenges described above, this study proposes a novel identification strategy to estimate the impact of wildfires. The approach exploits plausibly exogenous variation in wildfires attributable to lightning strikes. Lightning strikes are among the most common causes of wildfires, and the timing and location of such ignitions appear to be as good as random. Therefore, this study uses the number of lightning strikes as an instrumental variable (IV) for wildfires. This study also uses wildfire data obtained from

[1] Rangel and Vogl (2019) shows that agricultural fires are positively associated with pregnancy outcomes, suggesting that the income effect from agricultural fires may improve health status.

the United States Forest Service (USFS), which reports fire size at the incident level, regardless of the pollutants emitted.

This study has two key findings. First, wildfires cause considerable air pollution. A 1 km^2 increase in wildfires emits various pollutants well above the national air quality standards at the county average. The impact is not limited to particulate matter but also includes gaseous pollutants, such as CO, NO_2, and O_3. In addition to criteria air pollutants, wildfire smoke contains many other toxic pollutants, such as 1,3-butadiene and benzene. The magnitude of the impact is substantially larger than the one found in the literature using satellite imagery data, especially for gaseous pollutants.

Second, wildfire smoke has unusual health effects. This study uses pregnancy outcomes as a measure of health because infants represent a vulnerable population, and adverse health effects occur not only early in life but also later in life (e.g., Currie et al., 2009; Almond and Currie, 2011; Currie et al., 2014). The results indicate that a 1 km^2 increase in wildfires 1 month before birth reduces birth weight by 21.2 grams and increases the number of low birth weight infants by 8.2 per 1,000 at the county level. The same increase in wildfires also reduces gestational age by 0.1 weeks and increases the number of preterm births by 14.6 per 1,000.

This study moves beyond the literature in Four ways. This study provides the first large-scale quasi-experimental estimates of the impact of wildfires on pollution and health at birth. Using county-month level panel data, approximately 60% of the US population is covered.[2] Since incident-level wildfire studies focus on a small number of severe wildfires, the external validity of the results is limited (Jayachandran, 2009; Moeltner et al., 2013; Fadadu et al., 2021).

Second, this novel identification strategy provides more accurate evidence on the impact of wildfire smoke.[3] Amjad et al. (2021) review the literature and do not support the association between wildfire smoke exposure and pregnancy outcomes. At the same time, they also indicate the results may be biased due to the endogeneity of wildfires and the measurement error of wildfire smoke. In addition to the existing evidence, this study finds

[2]This study covers all counties that have populations exceeding 100,000 people.
[3]Butsic et al. (2017) propose a similar IV strategy, although they only use simulated data.

that debris and open burning are positively associated with pregnancy outcomes, suggesting that the income effect from agricultural fires may improve health status. The IV strategy thus addresses the endogeneity of wildfires and provides more rigorous evidence on the adverse health effects of wildfire smoke.

Third, this study adds to the wildfire literature which uses NOAA's Hazard Mapping System (HMS) smoke data. The HMS smoke data are commonly used in the literature on the impact of wildfire smoke on health and the economy (Borgschulte et al., 2022; Heft-Neal et al., 2022, 2023; Molitor et al., 2023; Cabral and Dillender, 2024; Miller et al., 2024). A limitation of the smoke plume observed by satellite imagery is that it overestimates the ground-level pollution level because a substantial portion of the smoke plume is above the ground (Liu et al., 2024)[4]. Figure 3 shows the HMS smoke, burned area, and the number of days that $PM_{2.5}$ exceeds the National Ambient Air Quality Standards (NAAQS) per year. The figure indicates that the number of days that $PM_{2.5}$ exceeds the National Ambient Air Quality Standards (NAAQS) is not necessarily associated with the HMS smoke, but the high concentration of $PM_{2.5}$ is concentrated in the burned area. Therefore, the incident-level wildfires can capture the high concentration of pollution around the burned area in comparison with the smoke plume observed by satellite imagery.

Finally, this study contributes to the existing literature on climate-economy literature. The number of lightning strikes is increasing due to global warming (Romps et al., 2014). Accordingly, lightning-initiated wildfires are also expected to increase (Pérez-Invernón et al., 2023). While many studies in the literature on climate change focus on the impact of temperature and precipitation, such as on agriculture and health (Dell et al., 2014; Carleton and Hsiang, 2016), this study indicates that the indirect impact of climate change on health through lightning-initiated wildfires. Thus, the results call for more attention to natural pollution rather than man-made pollution due to climate change.

[4]Childs et al. (2022) construct a model to estimate the ground-level $PM_{2.5}$ concentration from the HMS smoke data. The smoke $PM_{2.5}$ variables are used to estimate the impact of wildfire smoke on emergency department visits (Heft-Neal et al., 2023), learning outcomes (Wen and Burke, 2022), behavioral responses (Burke et al., 2022). However, they do not focus on pollutants other than $PM_{2.5}$, such as CO, NO_2, and O_3.

The rest of the paper is organized as follows. Section 2 provides a brief background on wildfires in the US and the potential impact of wildfires on air pollution and health. Section 3 describes the data used in this study. Section 4 presents the empirical strategy in detail. Section 5 reports the estimation results. Section 6 discusses the results in comparison with the existing literature. Section 7 concludes.

2 Background

2.1 Wildfires in the US.

According to the US Department of Agriculture, the term wildfire refers to "unplanned fires that occur in wildlands such as forests, rangelands or grasslands".[5] To date, wildfires have occurred in many places in the US. The number of wildfires from 2003 to 2018 totaled approximately 1.3 million, and the total area burned was 372,949km^2 (Short, 2021). Since the forest area in the US totals approximately 3.1 million km^2[6], a significant portion of wild land is affected by wildfires.

Wildfires can be classified into two categories by cause: human-caused wildfires and natural-caused wildfires. Human-caused wildfires include open burning and arson, while natural-caused wildfires are mainly caused by lightning strikes that ignite a tree or other fuel source. Table 1 reports the summary statistics for wildfire size by cause. In terms of number, the main causes of wildfires are debris and open burning and arson/incendiarism, which account for approximately 23% and 14%, respectively. In terms of the total area burned, natural-caused wildfires are one of the main sources[7]. Natural-caused wildfires are significantly larger than human-caused wildfires, and severe fires are likely to be caused by lightning strikes.

Wildfires occur throughout the US. Figure 1 shows (a) the distribution of wildfires larger than 1 km^2 and (b) the distribution of the total burned area. Figure 1 (a) and

[5]USDA: https://www.climatehubs.usda.gov/taxonomy/term/398

[6]DataBank, World Bank: http://databank.worldbank.org/data/reports.aspx?source=2&type=metadata&series=AG.LND.FRST.K2

[7]The naturally occurring wildfires are most frequently caused by lightning. There are also volcanic, meteor, and coal-seam fires.

Table 1: Summary Statistics: Wildfire Size (km^2) by Cause (2003–2018)

	Obs.	Mean	S.D.	Max	Sum
Arson/incendiarism	160,616	0.1	3.2	649.0	21,354.9
Debris and open burning	314,056	0.1	1.6	658.4	19,161.4
Equipment and vehicle use	107,715	0.2	8.5	1,660.0	26,027.7
Firearms and explosives use	1,867	1.1	11.6	331.1	2,112.1
Fireworks	12,456	0.1	2.7	196.2	1,234.2
Missing data/not specified/undetermined	366,496	0.2	10.0	2,681.9	86,729.1
Misuse of fire by a minor	31,687	0.0	1.3	155.2	1,089.0
Natural (including lightning)	174,132	1.1	19.0	2,258.9	188,647.0
Other causes	6,517	0.2	6.8	365.4	1,446.7
Power generation/transmission/distribution	24,006	0.4	9.1	801.2	10,329.9
Railroad operations and maintenance	11,375	0.1	0.9	46.1	886.9
Recreation and ceremony	53,871	0.2	11.8	2,177.4	12,238.5
Smoking	31,498	0.1	2.0	236.7	1,629.0
TOTAL	1,296,292	0.3	9.6	2,681.9	372,886.4

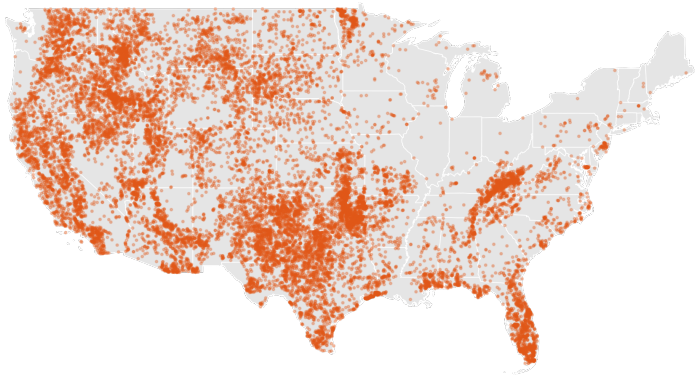
Notes: This table reports the summary statistics of wildfire size (km^2) by cause. The observational unit is the event of each wildfire. Each column indicates the number of observations (Obs.), mean (Mean), standard deviation (S.D.), maximum (Max), and summation (Sum).

(b) shows that wildfires occur in a wide range of areas. In particular, large wildfires are disproportionately distributed in western regions such as California, Oregon, and Washington State. In addition, southern regions such as Texas and Florida also face large wildfires.

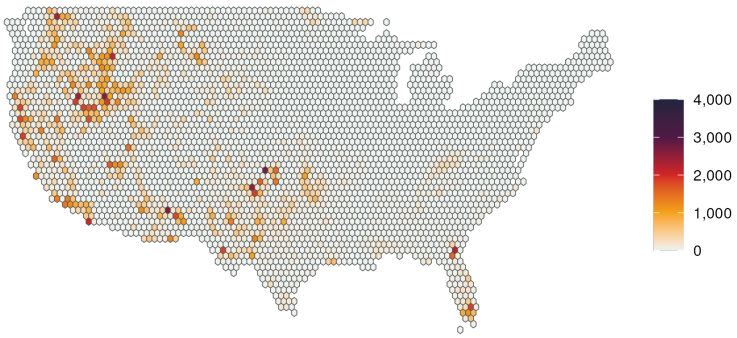
2.2 Climate Change and Wildfires

Recently, the risk of wildfires has increased due to climate change. Abatzoglou and Williams (2016) show that the increase in temperature and vapor pressure deficit enhance fuel aridity across the western US over the past several decades. They also find that increased fuel aridity contributed to an additional 4.2 million ha of forest fire area during the 1984–2015 period.

Since the size of wildfires is increasing due to climate change, air quality is deteriorating in the US. Xie et al. (2022) report that enhanced wildfire activity could cause a twofold to threefold increase in $PM_{2.5}$ over the US Pacific Northwest region during August through September without climate warming mitigation. McClure and Jaffe (2018) also indicate a decrease in $PM_{2.5}$ over most of the US but a positive trend in the 98th quan-



(a) Wildfires > 1 km^2.



(b) Total Burned Area (km^2).

Figure 1: Geographic Distribution of Wildfires and Lightning Strikes in the Continental US Over the 2003–2018 Period.

tile of $PM_{2.5}$ across the Northwest region due to wildfires. In addition, climate change affects wildfires through lightning strikes. Romps et al. (2014) report that the number of lightning strikes will increase in the US due to global warming. Pérez-Invernón et al. (2023) also shows that lightning-initiated wildfires are expected to increase.

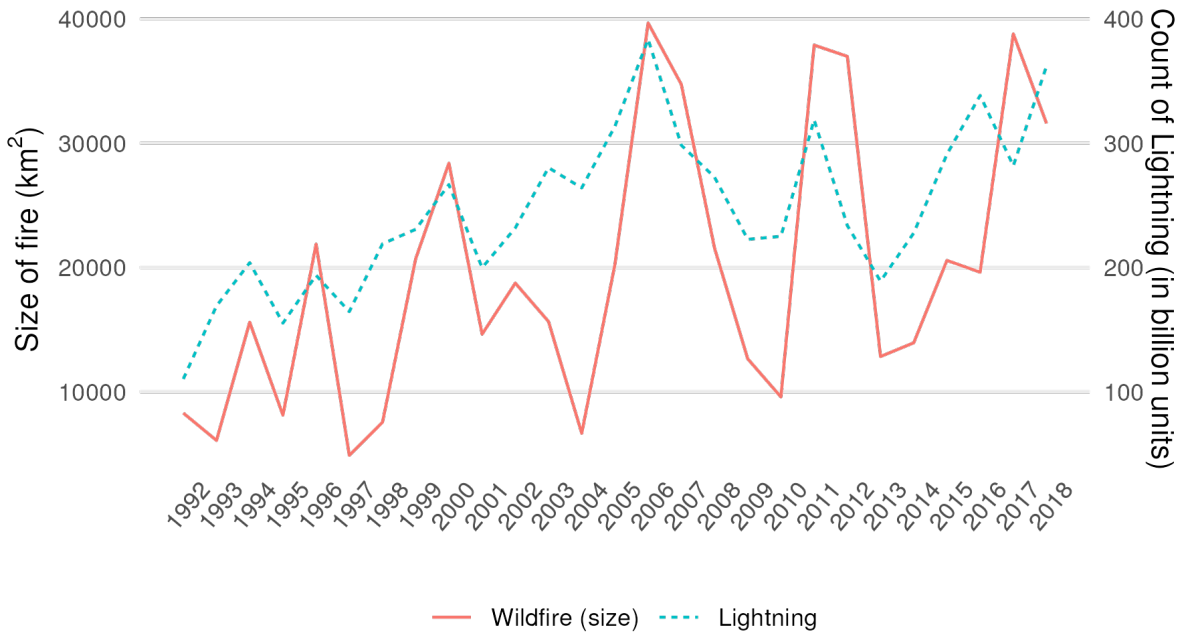


Figure 2: Annual Trends of Wildfires and Lightning Strikes.

Figure 2 displays the annual trends of wildfires and lightning strikes. This figure shows the strong association between wildfires and lightning strikes. The number of lightning strikes significantly increases when destructive wildfires occur. In addition, the number of lightning strikes has increased over time. The average number of lightning strikes was 181 billion per year from 1992 to 1999 and 274 billion per year from 2000 to 2018. Consistent with Romps et al. (2014), the number of lightning strikes has increased over time, possibly due to global warming.

To summarize, the impact of climate change on wildfires through lightning strikes can be significant. Since lightning strikes can be confounded by weather variables, such as temperature and humidity, this study examines the impact of lightning strikes on wildfires while controlling for weather variables in a later section.

2.3 Impact of Wildfires on Air Pollution and Health

Wildfires are a typical source of air pollution in the US. Naeher et al. (2007) review the literature on health-damaging pollutants from biomass combustion (Table A.1). The substances emitted from biomass combustion can be classified by compound type as particulate matter (PM), inorganic gases, or VOCs.

Examples of the PM include PM_{10}, $PM_{2.5}$.[8] PM can travel thousands of kilometers, dispersing the adverse health effects of pollution (Langmann et al., 2009). The potential health impact of PM include inflammation, oxidative stress, and allergies. Because PM comprises small particles, they can reach deep into the lungs; some can even enter the bloodstream. Exposure to these pollutants can cause problems such as heart or lung disease, irregular heartbeats, and asthma.

Figure 3 shows the distribution of wildfire smoke and $PM_{2.5}$ concentration. Figure 3a shows the NOAA's Hazard Mapping System (HMS) smoke, which is commonly used in the literature on the impact of wildfire smoke on health and the economy (Borgschulte et al., 2022; Heft-Neal et al., 2022, 2023; Molitor et al., 2023; Cabral and Dillender, 2024; Miller et al., 2024). The figure indicates that the smoke plume travels thousands of kilometers, dispersing in regions where wildfires do not occur, especially in the central region of the US. However, the smoke plume may not accurately measure the ground-level pollution level because a substantial portion of the smoke plume is above the ground (Liu et al., 2024). Figure 3b shows the number of days that $PM_{2.5}$ exceeds the National Ambient Air Quality Standards (NAAQS) per year. In contrast to the HMS smoke, the high concentration of $PM_{2.5}$ is concentrated on the burned area, such as California and the Northwest region.

Wildfires also emit inorganic gases, such as CO and NO_x[9] due to incomplete combustion and the high-temperature oxidation of nitrogen. O_3 is a compound of complex interactions between NO_x and VOCs that occur in the presence of heat and sunlight. The health problems that CO, NO_x, and O_3 can cause are asphyxiation, irritation, and

[8] PM_{10} and $PM_{2.5}$, which are mixtures of various particles with diameters smaller than 10 or 2.5 micrometers.

[9] NO_x is a collective term used to refer to nitrogen monoxide (NO) and nitrogen dioxide (NO_2).

respiratory morbidity.

Although many economic studies focus on PM and several inorganic gases (e.g., Deryugina et al., 2019; He et al., 2020; Borgschulte et al., 2022), wildfires emit many other pollutants. VOCs are organic chemical compounds whose composition allows them to evaporate under normal indoor atmospheric conditions of temperature and pressure.[10] Examples of health-damaging VOCs are 1,3-butadiene, benzene, styrene, and x-hexane. The health effects of these pollutants include irritation, oxidative stress, and inflammation. In addition, these pollutants are carcinogens.

With respect to the impact of pollution on health at birth, the epidemiological and economic literature indicates that exposure to CO, NO_2, PM_{10}, $PM_{2.5}$, and O_3 increases the odds of low birth weight.[11] However, the biological relationship between these pollutants and perinatal health remains poorly understood. One possible mechanism is that systemic oxidative stress from pollutants may reduce the fetal-placental exchange of oxygen and nutrients. In addition, pollutants may cause maternal lung and placental inflammation, leading to premature contractions and membrane rupture. Blood viscosity and coagulability may also slow fetal growth and increase the risk of maternal cardiovascular events, preeclampsia, and preterm delivery.

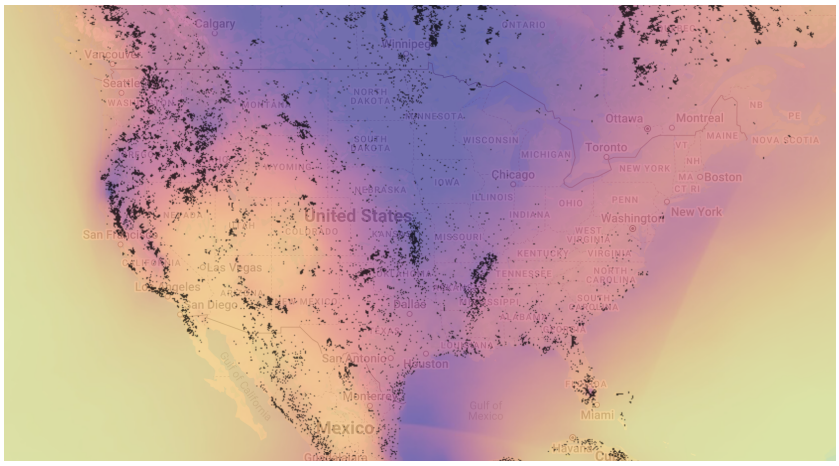
3 Data

3.1 Wildfire, Weather, and Lightning Strikes

Wildfire data were retrieved from the United States Forest Service (USFS) wildfire database, which was constructed by multiple federal and local agencies from 1992 to 2018 (Short, 2021). This database reports various information about wildfire events, such as latitude, longitude, discovery date, final fire size, and cause of fires. To construct a county-level variable, fire size is aggregated within each county and 50 km from the geographic center of each county. The average area of a US county is 2509 km^2. Previous

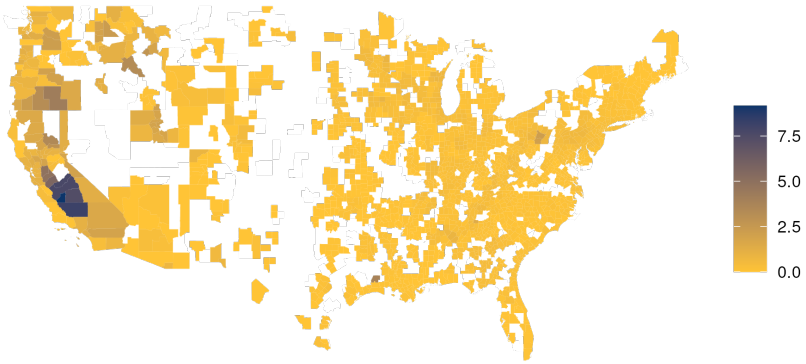
[10] US EPA, Technical Overview of Volatile Organic Compounds: https://www.epa.gov/indoor-air-quality-iaq/technical-overview-volatile-organic-compounds

[11] Stieb et al. (2012) review the literature in the field of epidemiology, and Currie et al. (2014) review the literature in the field of economics.



(a) NOAA's Hazard Mapping System (HMS) smoke

The colors from yellow to violet indicate the maximum smoke duration in hours from 0 to 500 and the black indicates the burned area: https://globalfires.earthengine.app/view/hms-smoke



(b) Number of days that $PM_{2.5}$ exceeds the NAAQS per year.

National Ambient Air Quality Standards for $PM_{2.5}$ is 35 $\mu g/m^3$ for 24-hour average.

Figure 3: Wildfire Smoke and Ground-Level $PM_{2.5}$ Concentration (2005-2024)

studies use wildfires detected from cell-level satellite imagery data. The limitation of the satellite imagery data used in previous studies is that the resolution is at least larger than 1 km^2, which may not accurately estimate the size of fires and pollution. Therefore, the USFS database is preferred for estimating the intensive margin of wildfire effects.

Weather condition data were obtained from the North American Regional Reanalysis (NARR) daily reanalysis data.[12] The NARR combines raw data from meteorological datasets, including those from airplanes, satellites, dropsonde (weather instruments dropped from aircraft), radiosonde (basically weather balloons), and land-based weather stations. These data are presented of 32-by-32-kilometer grids. Weather variables include pressure, temperature, humidity, precipitation, u-wind, and v-wind. The u-wind and v-wind variables are used to construct the wind direction and wind speed variables.[13] These variables are converted to the average of grids within counties and 50 km from the geographic center in each county, as well as a wildfire variable.

Daily lightning count data were derived from the National Lightning Detection Network (NLDN) flash data.[14] These data consist of more than 100 remote ground-based sensing stations located across the US that instantaneously detect the electromagnetic signals emitted when lightning strikes the Earth's surface. While lightning can be classified into cloud-to-cloud and cloud-to-ground lightning, NLDN data include only cloud-to-ground lightning, which is a potential cause of wildfires. Since lightning data are summarized by counts in 0.1-degree tiles for each day, these data are aggregated by county, as are the other variables.

3.2 Air Pollution

Air pollution data were collected from the Air Quality System database provided by the Environmental Protection Agency (EPA), which provides daily monitor-level data

[12]NCEP NARR: https://psl.noaa.gov/data/gridded/data.narr.html

[13]The relationships are as follows: wind speed $= (u^2 + v^2)^{\frac{1}{2}}$ and wind direction $= 180 + atan2(v, u) \cdot (\frac{180}{\pi})$, where v and u are v- and u-wind, respectively. $atan2(x, y)$ is a function of arctangent, which measures an angle from point(x, y).

[14]Severe Weather Database Inventory (SWDI) Lightning Tile Summaries: https://www.ncei.noaa.gov/products/lightning-products

for pollutants regulated under the Clean Air Act[15]. A variety of pollutants are used in this study (the number of counties available in the data is shown in parentheses): PM_{10} (1379), $PM_{2.5}$ (1873), CO (826), O_3 (2014), NO_2 (1007), and numerous VOCs (1,3-butadiene (859), benzene (965), styrene (905), n-hexane (616), and non-methane VOCs (NMVOCs) (406)).[16] Since the location of the monitors is available, pollution data are the average of the monitors within each county and 50 km from the geographic center in each county.

The EPA sets National Ambient Air Quality Standards for six major pollutants.[17] The units of measurement for the standards are parts per billion (ppb), parts per million (ppm), and micrograms per cubic meter ($\mu g/m^3$). The standards for PM_{10} and $PM_{2.5}$ are $150\mu g/m^3$ and $35\mu g/m^3$ for a 24-hour average, respectively. The standards for other pollutants are 9 (35) ppm for an 8 (1)-hour average of CO, 100 for a 1-hour average of NO_2, and 70 ppb for an 8-hour average of O_3. Notably, the standards are set by the rarity of the pollution level, not by the harmfulness. For instance, the standard for CO is set to no more than once per year. Hence, even if a pollution level is lower than the standard, it can still be harmful.

3.3 Pregnancy Outcomes, Mortality, and Maternal Risk Factors

Birth data were retrieved from the WONDER database provided by the Centers for Disease Control and Prevention (CDC), which reports monthly birth data across counties from 2003.[18] The birth data aggregated by county and month are available for the 2003–2018 period. The data are available for counties with populations of more than 100,000 people based on the 2000 census; others are excluded due to privacy restrictions. Moreover, observations numbering less than 10 are suppressed due to privacy policy. In such cases, these observations are replaced by 5. In total, data for 576 counties are available. The birth data are recorded at the mother's legal residence at the time of

[15] Air Data, EPA: https://aqs.epa.gov/aqsweb/airdata/download_files.html

[16] NMVOCs are a set of organic compounds that are typically photochemically reactive in the atmosphere and are characterized by the exclusion of methane. NMVOCs include a large variety of chemically different compounds, such as benzene and formaldehyde.

[17] EPA NAQS Table: https://www.epa.gov/criteria-air-pollutants/naaqs-table

[18] CDC WONDER: https://wonder.cdc.gov

birth. For pregnancy outcomes, this study uses the county average birth weight and gestational age because they are important health indicators for newborn and pregnancy outcomes. In addition, the number of low birth weight infants and preterm births at the county-month level are used as health outcomes.

In addition to pregnancy outcomes, two groups of control variables, maternal characteristics and birth characteristics, were collected. Mother characteristics include the average age, Hispanic origin (i.e., number of Hispanic or Latino mothers), race (i.e., number of American Indian or Alaskan Native, Asian or Pacific Islander, Black or African American, and White mothers), and marital status (i.e., number of married and unmarried mothers). The birth characteristics include medical attendants (i.e., number of births attended by a doctor of medicine, doctor of osteopathy, certified nurse midwife, and others), gender (i.e., number of male and female births), average live birth order, delivery method (i.e., number of vaginal and cesarean births), birthplace (i.e., number of births in hospital, freestanding birth center, and residence), and pluralities (i.e., average pluralities).

Maternal risk factor data (i.e., tobacco use, pregnancy-associated hypertension, diabetes, and eclampsia) are also retrieved to estimate heterogeneous effects and to use maternal health as another outcome. Neonatal mortality data are also collected from the CDC WONDER database for use as a health outcome. This study uses the first day and first year of mortality as neonatal mortality.

4 Empirical Strategy

4.1 Identification Issues

The objective of this study is to estimate the impact of wildfires on pollution and health. However, treating variations in wildfires as exogenous to pollution and human health is controversial because of the following concerns.

First, many wildfires classified as human-caused wildfires may be associated with important determinants of health at birth. For example, open burning may be associated

Table 2: Summary Statistics

	Obs.	Mean	S.D.	Min	10th %	90th %	Max
Panel A. Wildfires and pollution							
Wildfire size (km^2)	18,163,152	0.0	3.5	0.0	0.0	0.0	3,673.2
Number of Wildfires	18,163,152	0.3	1.0	0.0	0.0	1.0	129.0
Number of Lightning	18,163,152	90.1	483.1	0.0	0.0	108.0	54,572.0
CO (ppm)	3,291,713	0.4	0.2	0.0	0.1	0.7	7.0
NO_2 (ppb)	3,871,331	9.1	6.8	0.0	2.0	18.2	179.4
$PM_{10}(\mu g/m^3)$	1,412,504	21.2	21.4	0.3	8.0	37.0	10,020.0
$PM_{2.5}(\mu g/m^3)$	4,039,140	10.4	6.4	0.0	4.1	18.5	411.7
O_3 (ppb)	8,666,533	31.6	11.2	0.0	17.4	46.2	107.6
1,3-Butadiene (ppb)	257,413	0.3	1.4	0.0	0.0	0.5	128.0
Benzene (ppb)	448,171	1.7	3.0	0.0	0.5	2.9	291.6
Styrene (ppb)	295,976	0.6	3.2	0.0	0.0	1.0	607.6
n-Hexane (ppb)	284,133	1.4	4.2	0.0	0.3	2.6	514.6
NMVOC (ppb)	410,221	112.0	186.7	0.0	19.3	220.0	7,036.4
Panel B. Wildfires and health							
Wildfire size (km^2)	671,328	1.2	21.3	0.0	0.0	0.8	3,686.7
Num. of Wildfires	671,328	8.1	18.3	0.0	0.0	23.0	575.0
Num. of Lightning	671,328	2,663.5	4,639.6	0.0	0.0	8,131.0	88,346.0
Ave. Birth Weight	103,080	3,279.5	76.4	2,861.2	3,182.5	3,375.1	3,604.2
Ave. Gestational Age (Weeks)	103,080	38.6	0.3	34.7	38.3	39.0	42.2
Live Births	103,080	487.6	790.2	43.0	116.0	1,013.0	14,014.0
Ave. Age of Mother	103,080	28.0	1.6	23.1	26.0	30.1	34.0
Num. of Tobacco Use	103,080	25.0	29.0	5.0	5.0	55.0	454.0
Low Birth Weight per 1,000	103,080	78.3	26.1	0.0	43.3	111.1	221.2
Premature per 1,000	103,080	116.9	34.8	0.0	76.9	157.8	714.3
Mortality (1st Day) per 1,000	596,544	0.8	1.9	0.0	0.0	5.0	45.0
Mortality (1st Year) per 1,000	521,976	0.8	2.2	0.0	0.0	5.0	52.0
Num. of Pregnancy-Associated Hypertension	90,126	24.0	33.2	0.0	5.0	51.0	539.0
Num. of Diabetes	91,597	28.4	41.8	0.0	5.0	61.0	672.0
Num. of Eclampsia	72,674	2.3	3.6	0.0	0.0	5.0	57.0

Notes: This table reports the number of observations (Obs.), mean, standard deviation (S.D.), minimum (Min) and maximum (Max), and tenth and ninetieth percentile. The observational unit of the sample in Panel A is at the county-date level. The observational unit of the sample in Panel B is at the county-month level.

with agricultural income effects that affect human health (Rangel and Vogl, 2019; He et al., 2020). Open burning is an inexpensive method for removing crop residues to facilitate timely planting and control pests and weeds. In addition, open burning is often implemented after harvesting, and harvesting can have positive income effects on farmers. If such temporary income improves health status, then the impact of wildfires can be underestimated. Another example is that wildfires are likely to occur in areas with high crime rates, which may have negative impact on health. One of the leading causes of wildfires is arson/incendiarism (see Table 1). In such areas, neighborhood disorders and fear may be negatively correlated with mental health status, which may impair pregnancy outcomes. If these disadvantages negatively affect health at birth, then the impact of wildfires can be overestimated.

Second, governments may predict the risk of fires and implement fire management activities in advance, which are associated with changes in air pollution and health status. Recently, fire forecasts are provided by the National Interagency Coordination Center (NICC)[19] in the US. These services perform a variety of functions, such as forecasting fire risk for the next 7 days and the next 4 months based on a variety of weather conditions. In addition, wildfire-affected states may be likely to introduce better fire management activities, improve air quality, and provide better health care. In the state of California, the California Department of Forestry and Fire Protection (CAL FIRE)[20] has implemented preventive measures for California's wildlands while maintaining the quality of California ecosystems.[21] If governments with strong incentives to improve fire management also have strong incentives to improve air quality and health outcomes, then the impact of wildfires can be overestimated.

Finally, people may migrate to an area with a lower risk of wildfire. Deschenes and Moretti (2009) find that migration is an important determinant of a population's exposure to extreme weather events over time in the US. If pregnant mothers who avoid areas with high risk of wildfires have better health care, then the impact of wildfires can

[19]Fire weather and climate, NICC: https://www.predictiveservices.nifc.gov/weather/weather.htm
[20]CAL FIRE: https://wildfiretaskforce.org
[21]Nowak et al. (2014) estimate that trees and forests in the conterminous US removed 17.4 million tons of air pollution in 2010, with human health effects valued at USD 6.8 billion.

be underestimated.

4.2 Instrumental Variable Estimation

To address these concerns, this study employs an instrumental variable (IV) strategy, using lightning strikes as an instrument for wildfires. Lightning is a natural cause of wildfires and is difficult to predict and prepare for in advance since it travels many miles randomly through the air and strikes only one spot on the ground. In addition, lightning strikes occur everywhere, even in remote areas that are difficult for firefighters to access. Table 1 shows that the mean and standard deviation of the size of natural-caused wildfires are significantly larger than those of all other fires. Since lightning-initiated wildfires are difficult to suppress, these fires cannot be confounded by fire management responses.

This study first estimates the impact of wildfires on ground-level air quality at the daily level. The baseline specification is as follows:

$$\ln Pollution_{cd} = \beta \ln Wildfire_{cd} + X_{cd}\gamma + \delta_c + \zeta_d + \varepsilon_{cd} \tag{1}$$

where $Pollution_{cd}$ is the average pollution level in county c on day d. The dependent variable is CO, NO_2, PM_{10}, $PM_{2.5}$, O_3, or a variety of VOCs. The independent variable is the logarithm of wildfire size ($\ln Wildfire_{cd}$). To avoid missing values, this study adds 0.001 to the wildfire size before taking the logarithm. The vector X_{cd} includes fire weather conditions (i.e., humidity, precipitation, temperature, and a set of all possible interactions among them)[22]. In addition, the lagged and lead fire weather conditions up to 3 days are included in the vector X_{cd}[23]. The other weather variables (i.e., air pressure, wind direction, and wind speed) are also included to check for weather-related confounders. The county fixed effects (δ_c) and date fixed effects (ζ_d) control for time-invariant confounders specific to a county and common time-varying shocks.

[22] National Wildfire Coordinating Group (2023) report that the four critical weather elements that produce extreme fires are low relative humidity, strong surface winds, unstable air, and drought.

[23] The number of lagged and lead variables are limited up to 3 days because of computational constraints.

Next, this study estimates the impact of wildfires on pregnancy outcomes at the county-month level. The specification is as follows:

$$Y_{cm} = \beta \ln Wildfire_{cm-1} + X_{cm}\gamma + \delta_c + \zeta_m + \varepsilon_{cm}, \tag{2}$$

where the dependent variable is the outcome of interest in county c in month m (Y_{cm}). Pregnancy outcomes are county-month averages of birth weight and gestational age. To estimate the impact of wildfires on pregnancy outcomes, the primary specification includes the logarithm of wildfire size 1 month prior to the birth month ($\ln Wildfire_{cm-1}$). To estimate the impact of wildfires in earlier gestation months, lagged wildfires are also used as an independent variable. As well as the pollution analysis, the vector X_{cm} includes fire weather conditions. County fixed effects (δ_c) and year-month fixed effects (ζ_m) control for time-invariant confounders specific to a county and common time-varying shocks. The county fixed effects control for time-invariant confounders specific to a county, such as forest area, soil condition, and geographic differences in health and pollution. The year-month fixed effects control for common time-varying shocks, such as changes in medical or environmental policies for wildfire management during the sample period.

The ordinary least squares (OLS) estimates of Eq.(2) are prone to bias due to the identification concerns described above. In addition, both Eq.(1) and Eq.(2) may suffer from attenuation bias due to measurement error in wildfire variable. Therefore, this study employs an IV strategy involving the use of lightning as an instrument for wildfires[24]. The specification for the first stage is as follows:

$$\ln Wildfire_{ct} = \alpha Lightning_{ct} + X_{ct}\lambda + \nu_c + \xi_t + \upsilon_{ct}, \tag{3}$$

where $Lightning_{it}$ is the number of lightning strikes in county i and period t. For the pollution analysis, the time period is daily, and for the pregnancy outcome analysis, the

[24]The IV model is estimated using the two-stage least squares (2SLS) estimation.

time period is monthly. X_{ct}, ν_c, and ξ_t are the same as in Eq.(1) and Eq.(2). Since the number of lightning strikes is correlated in time, lagged and lead lightning strikes for 3 days for pollution analysis and 5 months for pregnancy analysis are included in the first stage[25].

5 Results

5.1 Lightning Strikes and Wildfires

Table 3 reports the impact of lightning strikes on wildfires at the county-date level. Columns 1 to 3 use the log of wildfire size as the dependent variable. A 1 standard deviation increase in the number of lightning strikes (i.e., 483) increases the burned area by 2.115%. Columns 4 to 6 use the number of wildfires as the dependent variable to examine the extensive margin effects. The impact of a 1 standard deviation increase in lightning strikes is only 0.024. Columns 2 and 5 indicate that weather controls other than fire weather variables have a negligible impact on the coefficients of lightning strikes. Finally, Columns 3 and 6 investigate the heterogeneous impact of lightning strikes on wildfires. The results suggest that lightning strikes lead to wildfires under global warming conditions; the impact it 5 times larger for a 1 standard deviation increase in temperature and 3 times larger for a 1 standard deviation decrease in humidity.

From the magnitude of the estimates, the intensive margin results suggest that large wildfires, such as more than 100 km^2, are more likely to be affected by lightning strikes. The extensive margin results also suggest that lightning strikes have a negligible impact on the number of wildfires. The results can indicate that lightning strikes create some smoldering fires that are not detected, and only a few of them grow into large wildfires. The results also show that the impact is more pronounced due to climate warming. Therefore, climate change significantly influences wildfires through lightning strikes during extreme weather.

[25]For pollution analysis, the number of lagged and lead variables are limited up to 3 days because of computational constraints.

Table 3: Lightning Strikes and Wildfires

	Size (km^2)			Count		
	(1)	(2)	(3)	(4)	(5)	(6)
Std. Num. of Lightning	0.021***	0.021***	0.002	0.024***	0.024***	0.031***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)
Std. Num. of Lightning × Std. Temp.			0.096***			0.094***
			(0.007)			(0.018)
Std. Num. of Lightning × Std. Precip.			-0.001***			-0.001***
			(0.000)			(0.000)
Std. Num. of Lightning × Std. Humidity			-0.053***			-0.068***
			(0.004)			(0.012)
County FE	X	X	X	X	X	X
Period FE	X	X	X	X	X	X
Fire Weather Controls	X	X	X	X	X	X
Other Weather Controls		X	X		X	X
Mean (Dep. var.)	0.041	0.041	0.041	0.271	0.271	0.271
SD (Dep. var.)	3.529	3.529	3.529	1.028	1.028	1.028
Counties	3108	3108	3108	3108	3108	3108
Obs.	18132072	18132072	18132072	18132072	18132072	18132072
R^2	0.174	0.174	0.174	0.190	0.190	0.191

Notes: The dependent variable is the log of wildfire size shown in Columns 1 to 3 and the number of wildfires shown in Columns 4 to 6. The unit of the sample is at the county-date level. Fire weather controls include humidity, precipitation, temperature, and a set of interactions of these variables. Other weather controls are pressure, wind speed, and wind direction. All controls are presented in logarithmic form except for wind direction. The 3-day lagged and leading weather variables and lightning variables are also included. All columns include county fixed effects and year-month-day fixed effects.

5.2 Wildfires and Air Pollution

Table 4 reports the effects of wildfires on air pollution using county-date level observations. All columns are the results of IV estimations using the number of lightning strikes as the instrument. Columns 1 and 2 use particulate pollutants as dependent variables, and Columns 3 to 10 use gaseous pollutants as dependent variables. All outcomes are the log of each pollutant concentration.

Table 4: Wildfires and Pollutants (IV), 2003-2018

	Particulate Pollutants		Gaseous Pollutants							
	PM_{10}	$PM_{2.5}$	CO	NO_2	O_3	1,3-Butadiene	Benzen	Styrene	n-Hexane	NMVOC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln Wildfire Size	0.115***	0.587***	0.378***	1.195***	0.808***	0.496***	0.602***	0.271**	1.511***	2.896*
	(0.033)	(0.046)	(0.053)	(0.117)	(0.061)	(0.130)	(0.103)	(0.119)	(0.290)	(1.488)
County FE	X	X	X	X	X	X	X	X	X	X
Daily FE	X	X	X	X	X	X	X	X	X	X
Fire Weather Controls	X	X	X	X	X	X	X	X	X	X
Kleibergen-Paap F-stat.	160.587	164.530	60.015	71.818	185.184	20.649	44.897	35.015	28.577	3.375
Mean (Dep. var.)	21.234	10.423	0.364	9.121	31.605	0.315	1.728	0.579	1.351	112.019
SD (Dep. var.)	21.398	6.441	0.239	6.767	11.203	1.408	3.017	3.161	4.151	186.653
Counties	1379	1871	826	1007	2014	851	951	888	581	205
Obs.	1412504	4039140	3291713	3871331	8666533	257413	448171	295976	284133	410221

Notes: All results are IV estimates, using the number of lightning strikes as an instrument. The dependent variables are the logarithm of each pollutants' concentration. The observational unit is at the county-date level. All estimations include fire weather controls, county fixed effects, and year-month-day fixed effects. Standard errors clustered by county are shown in parentheses.

All wildfire coefficients are positive and statistically significant. At the average of

the sample[26], the causal effects of a 1 km^2 increase in wildfires are 126% for CO, 398 % for NO_2, 38% for PM_{10}, 196% for $PM_{2.5}$, and 269% for O_3. In addition, VOCs are also emitted by wildfires, and the effects are statistically significant. A 1 km^2 increase in wildfire burning emits 1,3-butadiene by 165%, benzene by 201%, styrene by 90%, n-hexane by 504%, and NMVOCs by 965%.

In sharp contrast with existing wildfire studies using satellite imagery data, the impact on gaseous pollutants are much larger. For example, Borgschulte et al. (2022) construct a wildfire smoke variable using satellite imagery. They find that one day smoke exposure increases $PM_{2.5}$ by nearly 40% of the standard deviation and CO and NO_2 by less than 10% of the standard deviation.[27] Therefore, the authors conclude that $PM_{2.5}$ is a signature pollutant of wildfire smoke. This study suggests that satellite imagery data can be measured with error, leading to underestimation of the impact of wildfires on pollution, especially for invisible pollutants.

Figure 4 also shows the event study results of wildfires on pollution, using lagged and leading wildfire variables.[28] The results show that the largest impact of wildfires on pollution occur on the day of the wildfire, and the impact are almost zero after 3 days for all pollutants. Therefore, the health impact of wildfire smoke is likely to be acute.

5.3 Wildfires and Health

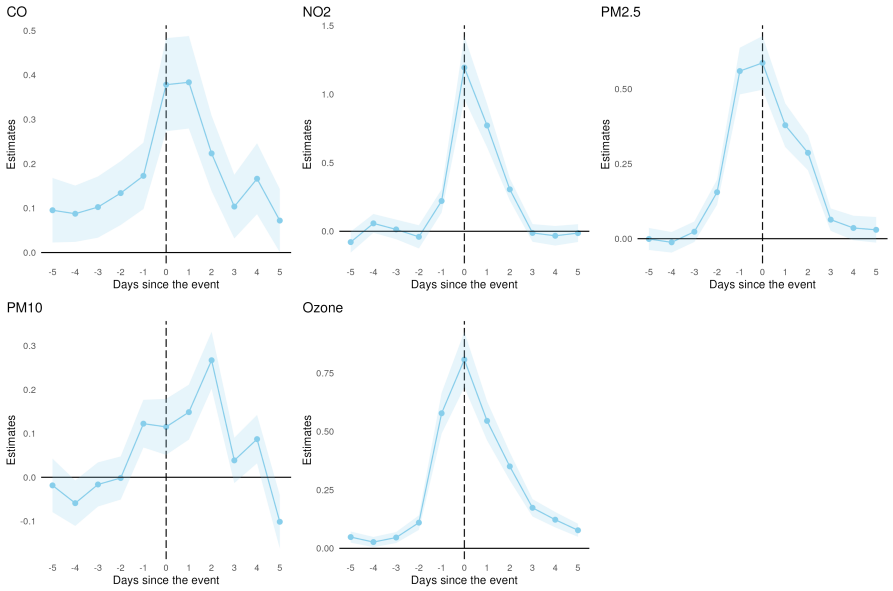
OLS Results by Cause of Wildfires.

Next, this study estimates the impact of wildfires on pregnancy outcomes using county-month level observations. Before IV estimation, this study first estimates the impact of wildfires on pregnancy outcomes by cause of wildfires, using OLS estimation.

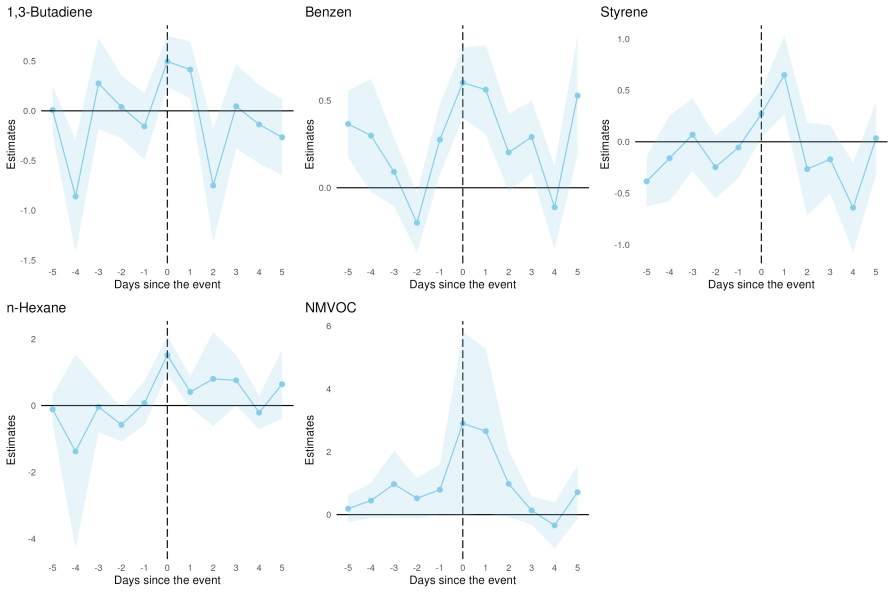
[26]Since the wildfire is a logarithmic variable, the impact of wildfires on pollution is calculated based on the average size of a wildfire (i.e., 0.3 km^2, see Table 1). Therefore, the impact of a 1 km^2 increase in wildfires is calculated by $\frac{\beta}{0.3}$.

[27]Borgschulte et al. (2022) construct a wildfire smoke variable that takes the value of 1 if the county is fully covered by smoke plumes. The mean and standard deviation of the smoke variable are 0.07 and 0.26, respectively. The mean and standard deviation are then 0.4 and 0.3 for CO (ppm) and 9.2 and 7.5 for NO_2 (ppb), respectively.

[28]The point estimates are obtained from the separate IV estimation. Therefore, the figure plots the point estimates from 11 separate IV estimations for each pollutant.



(a) Criteria Pollutants



(b) Volatile Organic Compounds (VOCs)

Figure 4: Wildfires and Pollution: Event Study (IV), 2003-2018

Table 5 reports the effects of wildfires on pregnancy outcomes by the top 5 causes of wildfires as the independent variables for each column. In these specifications, other fires are used as the control variable. Panels A, B, C, and D use average birth weight, number of low birth weight (i.e., $<$ 2500 gram), average gestational age, and preterm birth (i.e., $<$ 38 weeks) as dependent variables, respectively. The results in column 1 show that the impact of natural-caused wildfires which are almost equivalent to lightning-initiated wildfires. These results suggest that natural-caused wildfires have a negative impact on pregnancy outcomes. For example, a 1 standard deviation increase in wildfire size is associated with a decrease of 0.8 grams in birth weight and a decrease of 0.0 weeks in gestational age at the average of the sample and these impacts are statistically significant at the conventional level. In addition, the rate of low birth weight and premature births are also increased by 0.0% and 0.4%, respectively.

In contrast to natural-caused wildfires, human-caused wildfires are positively associated with pregnancy outcomes in consistent with the identification issues. The positive association is likely to be driven by the income effects of open burning. Other human-caused wildfires, such as equipment and vehicle use and recreation and ceremony, are also positively associated with pregnancy outcomes. One exception is that arson/incendiarism is negatively associated with pregnancy outcomes. This is also consistent with the identification issues because arson/incendiarism is likely to occur in areas with high crime rates, which may have negative impact on health.

IV Results.

Table 6 estimates the effects of wildfires on pregnancy outcomes, using county-month-level panel data. There are two reasons why this study uses IV estimation in addition to the OLS estimation using natural-caused wildfires. First, the cause of many wildfires are unspecified, which may lead to the bias due to measurement error. As shown in Table 1, approximately 30% of wildfires are unspecified. If the specified wildfires are not randomly distributed, the OLS estimates can be biased. Even if the measurement error is random, the OLS estimates can be suffered from attenuation bias. Therefore, the IV estimation

Table 5: Wildfires and Pregnancy Outcomes by Cause of Wildfires (OLS), 2003-2018

	Natural	Debris	Arson	Equipment	Recreation
	(1)	(2)	(3)	(4)	(5)
Panel A: Birth Weight (Mean = 3279 grams, SD = 76)					
Ln Wildfire Size (t - 1)	-0.236**	0.078	-0.012	0.155	0.127
	(0.105)	(0.122)	(0.113)	(0.129)	(0.163)
R^2	0.674	0.674	0.674	0.674	0.674
Panel B: Low Birth Weight per 1,000 (Mean = 39, SD = 63)					
Ln Wildfire Size (t - 1)	0.005	-0.041	0.011	-0.126**	-0.159**
	(0.051)	(0.056)	(0.051)	(0.057)	(0.076)
R^2	0.343	0.343	0.343	0.343	0.343
Panel C: Gestational Age (Mean = 39 weeks, SD = 0.3)					
Ln Wildfire Size (t - 1)	-0.001**	0.001	-0.001	0.000	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
R^2	0.504	0.504	0.504	0.504	0.504
Panel D: Premature per 1,000 (Mean = 58, SD = 92)					
Ln Wildfire Size (t - 1)	0.130*	-0.017	0.065	-0.135	-0.124
	(0.072)	(0.107)	(0.089)	(0.092)	(0.119)
R^2	0.370	0.370	0.370	0.370	0.370
County FE	X	X	X	X	X
Year-Month FE	X	X	X	X	X
Fire Weather Controls	X	X	X	X	X
Counties	576	576	576	576	576
Obs.	103080	103080	103080	103080	103080

Notes: The dependent variables are county average birth weight (grams), county total number of low birth weight infants per 1,000, county average gestational age (weeks), and county total preterm births per 1,000. The observational unit is at the county-month level. All estimations include fire weather controls, 5 months lagged and leading lightning strikes, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses. Ln Wildfire Size (t-1) is the logarithm of wildfire size 1 month prior to the birth month and each column uses the top 5 causes of wildfires as the independent variables. The top 5 causes of wildfires are natural, debris and open burning, arson/incendiarism, equipment and vehicle use, and recreation and ceremony.

can provide more accurate estimates.

Columns 1 through 3 use average birth weight as the outcome, and Columns 5 through 7 use average gestational age as the outcome. The OLS results shown in Columns 1 and 5 indicate that wildfires are positively associated with birth weight and negatively associated with gestational age. At the average of the wildfire, a 1 km^2 increase in wildfires is associated with an increase of 0.1 grams in birth weight[29]. The impact of the same increase in wildfires on gestational age is almost zero.

Table 6: Wildfires and Pregnancy Outcomes (OLS & IV), 2003-2018

	Birth Weight (Grams)			Low Birth Weight per 1,000	Gestational Age (Weeks)			Premature per 1,000
	OLS	IV	IV	IV	OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln Wildfire Size (t - 1)	0.037	-6.345***	-6.265***	2.458***	0.000	-0.034***	-0.034***	4.275**
	(0.085)	(1.924)	(1.907)	(0.936)	(0.000)	(0.013)	(0.013)	(1.917)
County FE	X	X	X	X	X	X	X	X
Year-Month FE	X	X	X	X	X	X	X	X
Fire Weather Controls	X	X	X	X	X	X	X	X
Other Weather Controls			X	X			X	X
Kleibergen-Paap F-stat.		44.1	45.0	45.0		44.1	45.0	45.0
Mean (Dep. Var.)	3279.471	3279.471	3279.471	78.304	38.628	38.628	38.628	116.910
SD (Dep. Var.)	76.443	76.443	76.443	76.443	0.302	0.302	0.302	0.302
Counties	576	576	576	576	576	576	576	576
Obs.	103080	103080	103080	103080	103080	103080	103080	103080
R^2	0.674	0.653	0.654	0.318	0.504	0.468	0.468	0.326

Notes: The dependent variables are county average birth weight (grams), county total number of low birth weight infants per 1,000, county average gestational age (weeks), and county total preterm births per 1,000. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

However, the negligible effects of wildfires appear to be biased when comparing OLS and IV estimates, which is consistent with the findings of Rangel and Vogl (2019) and He et al. (2020). The IV estimation shown in Column 2 suggests that wildfires have negative and significant effects on birth weight. The results indicate that a 1 km^2 increase in wildfires reduces birth weight by 21.2 grams at the average of the wildfires. In addition, the same increase in the size of wildfires reduces the gestation period by 0.1 weeks. Columns 3 and 7 present the results, including additional weather controls, which have negligible impact on the IV estimates.

Columns 4 and 5 of Table 6 report the effects of wildfires on the number of low birth weight infants (below 2500 grams) and preterm (below 38 weeks) births. A 1 km^2 increase

[29]Since the wildfire is a logarithmic variable, the impact of wildfires on pregnancy outcomes is calculated based on the average size of a wildfire (i.e., 0.3 km^2, see Table 1). Therefore, the impact of a 1km^2 increase in wildfires is calculated by $\frac{\beta}{0.3}$.

in wildfires increases the incidence of low birth weight by 8.2 per 1,000 and the incidence of preterm birth by 14.6 per 1,000.

Dynamic effects.

Table 5 reports estimates of the effects of wildfires at the earlier gestation periods. The estimates are obtained from separate IV estimations for each pregnancy outcome. Therefore, the figure plots the point estimates from 14 separate IV estimations for each pregnancy outcome.

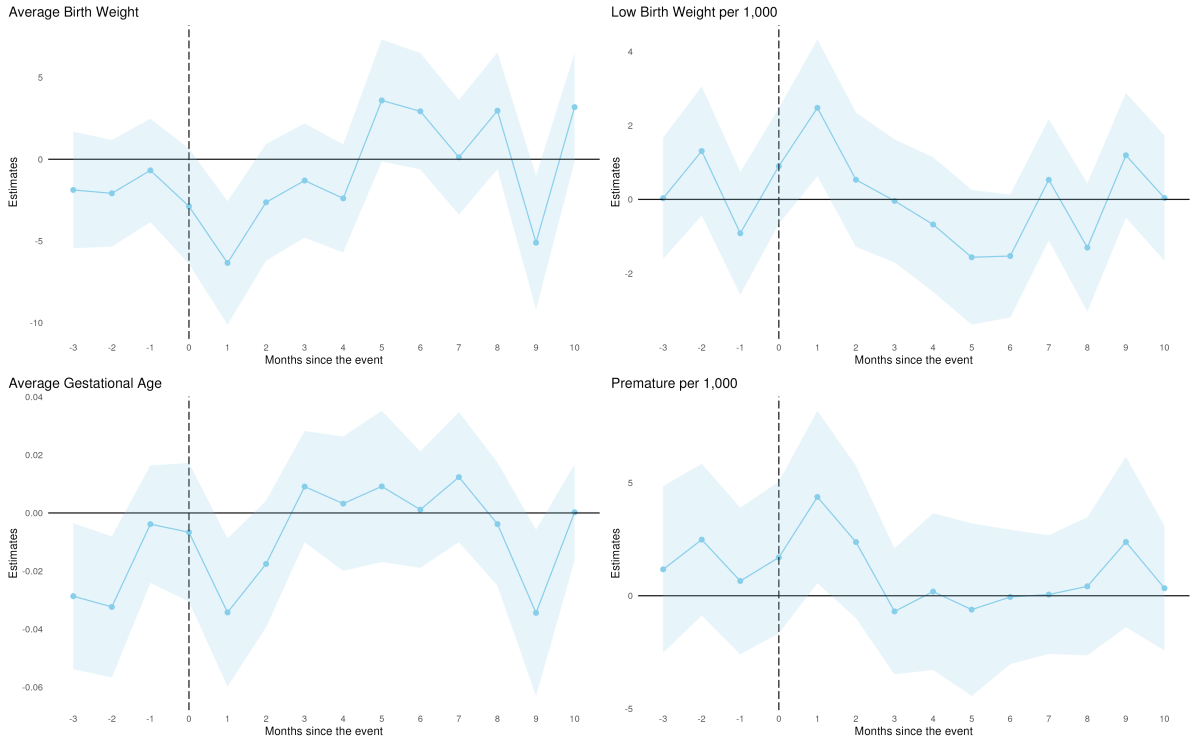


Figure 5: Dynamic Effects of Wildfires on Pregnancy Outcomes (IV), 2003-2018

The patterns in Table 5 reveal that the largest effects are for 1 month prior to birth. Thereafter, the effects decrease for earlier gestation periods and the effects are almost zero after 3 months. One exception is the effects 9 months prior to birth, which are larger than those for 8 months prior to birth and are statistically significant at the 5% level for birth weight and gestational age. These results are consistent with those of Rangel and Vogl (2019), who showed that agricultural fires 0–12 weeks and 26–38 weeks before birth have negative effects on birth weight. In contrast, such fires 13–25 weeks before birth have positive or no effects on birth weight.

Mortality and Maternal Risk Factors

Table 7 reports the impact of wildfires on mortality and maternal risk factors. Column 1 uses the number of live births per 1,000 population, which is used as a broader proxy for in utero survival, a strategy similar to that used in (Jayachandran, 2009; Rangel and Vogl, 2019). At the sample mean of wildfires and births, a 1 km^2 increase in wildfires reduces the number of live births by approximately 0.0.

For postnatal mortality, Columns 2 and 3 use the number of infants who died within a day or a year of birth per 1,000 population. The results indicate that a 1 km^2 increase in wildfires increases the number of mortality within the 1st day by 0.0 and the 1st year by 0.0, although these are statistically not significant.

Regarding maternal risk factors, Columns 4 to 6 use the number of mothers who reported maternal risk factors. The reasons for using maternal risk factors as outcomes are (1) to clarify the mechanism of wildfire effects on health at birth and (2) to estimate the effects on maternal health itself. The results indicate that a 1 km^2 increase in wildfires decreases pregnancy-associated hypertension by 0.0 and increases eclampsia by 0.6 per 1,000. However, these point estimates are small and not statistically significant at the conventional level.

Table 7: Additional Outcomes (IV), 2003-2018

	Mortality			Maternal Risk Factors		
	Live Births per 1,000 (1)	1st Day per 1,000 (2)	1st Year per 1,000 (3)	Hypertension per 1,000 (4)	Diabetes per 1,000 (5)	Eclampsia per 1,000 (6)
Ln Wildfire Size (t - 1)	-0.026***	0.015	0.000	0.048	2.031**	0.587
	(0.006)	(0.022)	(0.002)	(1.008)	(0.891)	(0.537)
County FE	X	X	X	X	X	X
Year-Month FE	X	X	X	X	X	X
Fire Weather Controls	X	X	X	X	X	X
Kleibergen-Paap F-stat.	44.1	127.9	128.8	49.2	49.7	40.7
Mean (Dep. Var.)	1.069	0.086	0.017	51.509	57.039	6.633
SD (Dep. Var.)	0.231	0.913	0.090	26.016	27.262	11.815
Counties	576	3107	3107	576	576	576
Obs.	103080	596544	521976	90126	91597	72674
R^2	0.809	0.654	0.041	0.451	0.450	0.169

Notes: The dependent variables are the county total number of live births, the county total number of mortality within a day and a year of birth, and the county total number of pregnant mothers who reports hypertension, diabetes, and eclampsia per 1,000. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

In contrast, the same increase in wildfires significantly increases diabetes by 2.0 per 1,000. A possible explanation is that people are less likely to go outside and exercise during wildfires, which may increase the risk of diabetes. Another explanation is that air pollution can directly increase the risk of diabetes. A systematic review by Yang et al. (2020) show that air pollutants are associated with increased odds of diabetes, including gestational diabetes.[30] Many studies have shown that gestational diabetes has adverse effects on health at birth. McIntyre et al. (2019) show that gestational diabetes causes health burdens, such as preterm birth, excessive birth weight, and clinical neonatal hypoglycemia. Therefore, wildfire may cause preterm birth in part due to gestational diabetes. However, because gestational diabetes can cause excessive birth weight, the mechanism underlying the effects of gestational diabetes on birth weight is unclear. McIntyre et al. (2019) also show that gestational diabetes causes maternal health burdens, such as maternal diabetes and eclampsia. Therefore, wildfires have negative impact not only on children but also on mothers.

Mechanism.

Wildfires can affect pregnancy outcomes through various mechanisms. One potential channel is that wildfires have adverse effects on pregnancy outcomes through mental health. Many studies examine the health effects of natural disasters, such as hurricanes and earthquakes, on pregnancy outcomes (e.g., Currie and Rossin-Slater, 2013; Kim et al., 2017; Menclova and Stillman, 2020; de Oliveira et al., 2023). They find that natural disasters have a negative impact on pregnancy outcomes through mental stress. Similarly, large wildfires can cause mental stress and have negative effects on pregnancy outcomes.

To examine the mental health channel, this study estimates the effects of wildfires on pregnancy outcomes excluding large wildfires. Appendix Table C.7 shows the impact of wildfires which are less than 10 km^2. Since the results are consistent with the baseline estimates, the baseline estimates are not driven by large wildfires. Therefore, the mental

[30]During pregnancy, a hormone made by the placenta prevents the body from using insulin effectively, and glucose builds up in the blood instead of being absorbed by the cells. As a result, pregnant women are more likely to suffer from diabetes.

health channel through large wildfires is not the main mechanism of wildfire effects on pregnancy outcomes.

This study also estimates the heterogeneous effects of wildfires to explore the mechanism. In the mental health literature, since single and younger mothers have characteristics that may leave them less financially and socially secure, they are more likely to be suffered from mental health problems after a natural disaster (Kim et al., 2017; Menclova and Stillman, 2020; de Oliveira et al., 2023). Other socio-economic status also can amplify the mental health effects. Alexander et al. (2017) review the literature on the racial differences in post-traumatic stress disorder (PTSD) after a natural disaster. They conclude that blacks are more likely to be suffered from PTSD because they have less social support after a disaster.

Another channel is that the impact of wildfires on individuals who have been temporarily displaced may be different. For example, after Hurricane Katarina, New Orleans lost black population and gained Hispanics and Asians (Plyer, 2011). However, since the birth data is recorded in the legal residence, the temporary evacuation does not affect where to record. A possible interpretation in this case is that the impact of wildfires can be underestimated due to temporary evacuation because the impact is the average of people who are exposed to wildfires and evacuate from wildfires. Another interpretation is that the impact of wildfires can be overestimated because the stress associated with evacuation due to wildfires may cause adverse health effects.

This study therefore estimates the heterogenous impact of wildfires based on socio-economic status. To examine the heterogeneous effects, the interactions between wildfires and maternal characteristics[31] are added to Eq.(2) as endogenous variables, and the interactions between lightning strikes and maternal characteristics are added to Eq.(3) as instruments.

Appendix Table C.3 to C.6 reports the results for heterogeneous effects of wildfires on pregnancy outcomes. Focusing on column 6 in all tables, this study does not find consistent evidence with the mental health literature. For example, the negative effects

[31] These interacted variables are used as the total number per 1,000 births.

of wildfires on all pregnancy outcomes are larger for older mothers. The negative effects on the number of low birth weight and premature are smaller for black mothers. The results therefore differ from the existing literature on the mental health effects of natural disasters. Although these are suggestive evidence, the results indicate that the mechanism of wildfires on pregnancy outcomes is not through mental health.

Robustness checks.

Table 8 implements robustness checks. As described in Section 4.1, there may still be concerns regarding the potential confounders, such as county-specific seasonality, county-specific weather conditions, and time-invariant county-specific fire management. To address these concerns, this study incorporates additional covariates and fixed effects.

As a robustness check, the maternal characteristics and birth characteristics are included in Columns 2 and 3. If wealthy mothers migrate from a wildfire-affected county, their socio-economic status may be a potential confounder. Therefore, this study controls for maternal characteristics, including the average age of mothers, Hispanic origin, race, and marital status, and birth characteristics, including medical attendant at birth, sex, average live birth order, delivery method, birthplace, and multiple births. Since the coefficients of wildfire are stable after controlling for maternal and newborn characteristics, concerns about a migration response are negligible.

Column 3 introduces county-specific seasonality. Lightning strikes may have county-specific seasonal patterns that are associated with agricultural production and income. To check the robustness to seasonality, the interactions between county fixed effects and dummy variables that take the value of 1 in each season (i.e., Jan. to Mar., Apr. to Jun., Jul. to Sep., Oct. to Dec.) are controlled. The results are not significantly different from the baseline estimates, suggesting that county-specific seasonality is not a concern.

Columns 4 and 5 introduce 1 month lagged weather controls and county-by-year fixed effects to take fire management activity into account. Past weather conditions are often used to predict fire weather.[32] In addition, county-by-year fixed effects are controlled to

[32]The Global Fire Weather Database (GFWED) analyzes various weather factors that lead to the start and spread of fires by combining meteorological data, such as temperature, humidity, wind speed, and

test for county-specific time-invariant fire management responses. Since these alternative specifications are not significantly different from the baseline estimates, the concerns are negligible.

Table 8: Robustness Checks (IV), 2003-2018

	Base model	Maternal Controls	Birth Controls	Season FE × County FE	Lagged weather	County FE × Year FE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Birth Weight (Grams)						
Ln Wildfire Size (t - 1)	-6.371***	-6.721***	-6.571***	-7.347***	-6.519***	-8.535***
	(1.933)	(1.940)	(1.935)	(2.819)	(2.050)	(3.111)
R^2	0.653	0.659	0.677	0.656	0.652	0.688
Panel B: Low Birth Weight per 1,000						
Ln Wildfire Size (t - 1)	2.485***	2.723***	2.540***	2.873**	2.579**	3.764**
	(0.946)	(0.965)	(0.946)	(1.382)	(1.006)	(1.642)
R^2	0.317	0.318	0.373	0.325	0.315	0.355
Panel C: Gestational Age (Weeks)						
Ln Wildfire Size (t - 1)	-0.034***	-0.036***	-0.035***	-0.052***	-0.036***	-0.032*
	(0.013)	(0.013)	(0.013)	(0.019)	(0.014)	(0.017)
R^2	0.467	0.469	0.487	0.438	0.464	0.589
Panel D: Premature per 1,000						
Ln Wildfire Size (t - 1)	4.389**	4.823**	4.577**	6.146**	4.477**	3.989*
	(1.955)	(2.003)	(1.981)	(2.794)	(2.049)	(2.165)
R^2	0.323	0.318	0.350	0.301	0.321	0.458
Kleibergen-Paap F-stat.	43.705	43.469	43.207	36.488	38.381	18.975

Notes: The dependent variables are county average birth weight (grams), county total number of low birth weight infants per 1,000, county average gestational age (weeks), and county total preterm births per 1,000. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

Furthermore, this study directly checks for violations of the exclusion restriction. Zou et al. (2020) show that thunderstorms increase emergency department visits for acute respiratory illnesses. If lightning strikes directly affect pregnancy outcomes, then the exclusion restriction is violated. To check this concern, this study conducts placebo tests. The placebo tests regress lightning strikes on pregnancy outcomes using a sample where wildfires were not observed[33]. Appendix Table D.8 reports that a 1 standard deviation increase in lightning strikes is associated with a decrease of 0.2 grams for birth weight, an increase of 0.0 per 1,000 for the number of low birth weight infants, a decrease of 0.0 weeks for gestational age, and an increase of 0.0 per 1,000 for the number of preterm births.

precipitation from satellite data.

[33]The mean and standard deviation (SD) of the number of lightning strikes in the sub-sample are 2,708 and 4,911, respectively

Therefore, the direct impact of lightning strikes on pregnancy outcomes is negligible.

Another concern is that two-way fixed effects (TWFE) regressions may be biased if treatment effects are heterogeneous across counties over time (de Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). In the case of IVs, the estimates may also suffer from bias because an IV estimate is the rate of the first-stage and reduced-form coefficients with the TWFE. To address this concern, this study uses an alternative estimator proposed by Borusyak et al. (2022). The estimator in Borusyak et al. (2022) is robust to bias due to the TWFE under parallel trends assumptions. Since the estimator is applicable for binary treatment, this study creates a dummy that takes a value of 1 when the number of lightning strikes exceeds 10,000 and 0 otherwise. Using the dummy as an IV, this study estimates first-stage and reduced-form regressions and calculates the Wald estimates.

The results are reported in Appendix Table E.1. The Wald estimate of the TWFE in Column 2 is similar to the estimates obtained using the number of lightning strikes as the instrument. Then, the Wald estimates based on the TWFE robust estimator of Borusyak et al. (2022) are shown in Column 4. Since the difference between the baseline and the Wald estimates are not significant, the TWFE estimates are robust to bias due to heterogeneous treatment effects.

This study also checks for issues related to taking logs of zeros since the results are sensitive to the unit choice (Chen and Roth, 2023). The problem arises because the percentage change from 0 is not defined. Therefore, following Chen and Roth (2023), this study explicitly defines the change from 0 to 1 as a certain percentage change. For this purpose, the wildfire size is transformed to $\ln\left(\frac{Wildfire}{Wildfire_{min}}\right)$ if $Wildfire > 0$ and to $-x$ if $Wildfire = 0$, where $Wildfire_{min}$ is the minimum wildfire size strictly larger than 0. This transformation can be interpreted as an approximate percentage effect, where an increase from 0 to $Wildfire_{min}$ is a $x \times 100\%$ increase. The results with different $x \in \{0, 0.1, 1, 3, 5\}$ values are reported in Appendix Table F.1. Since the results are robust to x, the definition of a change from 0 is not a concern.

Finally, this study estimates the main results using Conley standard errors which are

robust to spatial correlation (Conley, 1999), since wildfires are highly spatially correlated. Appendix Table G.1 shows the results using the standard errors allowing for 100 km of spatial correlation. The results are not significantly different from the baseline estimates.

6 Discussion

In this section, this study compares the magnitudes of the effect sizes in the existing literature. One straightforward approach is to calculate the health effects per unit of pollutant. To do so, the health effects are divided by the pollution effects.

Table 9 summarizes the results in the existing literature. Currie and Walker (2011) show that the traffic congestion increases NO_2 by 10.8% and the incidence of low birth weight by 9.3 per 1,000. Another study by Rangel and Vogl (2019) shows that a 1 standard deviation increase in agricultural fires increases PM_{10} by 18.7 $\mu g/m^3$ on a weekly basis and decreases the incidence of low birth weight by 35 per 1,000 if the fires occur 0–12 weeks before birth continuously. Alexander and Schwandt (2022) show that emissions cheating cars increase PM_{10}, $PM_{2.5}$, and O_3 by 2.2%, 2%, and 1.3% and decrease the incidence of low birth weight by 19 per 1,000.

In comparison with a unit increase effect on low birth weight, the effects of wildfires are smaller than those of other pollutants. The effect of traffic congestion is 5 per 1 ppb (NO_2) (Currie and Walker, 2011). The effect of emissions cheating cars on low birth weight is 44 per 1 $\mu g/m^3$ (PM_{10}), 95 per 1 $\mu g/m^3$ ($PM_{2.5}$), and 48 per 1 ppb (O_3) (Alexander and Schwandt, 2022). In contrast, this study shows that wildfires increase PM_{10}, $PM_{2.5}$, NO_2, and O_3 by 38 $\mu g/m^3$, 43 $\mu g/m^3$, 69 ppb, and 180 ppb on a 3-day basis since wildfires occur.

The explanation for the smaller effects of wildfire pollutants is that the impact of wildfires is acute in contrast to traffic emissions. The impact of wildfire smoke on pollution is the highest on the day of the wildfire and almost zero after 3 days. Therefore, the health effects of wildfires can be caused by short-term exposure to severe pollution[34]. If the short-term severe pollution has smaller health effects than long-term moderate pollution, the

[34]The average number of wildfires in a month is 8.1

effects of wildfires can be smaller than those of other pollutants.

The exception is that the effect of agricultural fires on low birth weight is 2 per 1 $\mu g/m^3$ (PM_{10}) (Rangel and Vogl, 2019). The possible explanation is the difference in a variety of pollutants emitted by wildfires and agricultural fires. Rangel and Vogl (2019) shows that agricultural fires increase PM_{10}, but not NO_x and O_3. Since the unit increase effect of PM_{10} in this study can be biased upward due to the positive correlation with other pollutants, it can be larger than agricultural fires.

Overall, a unit increase effect on low birth weight is not significantly different from the existing literature, underlining the robustness in the pollution effects of wildfires on pregnancy outcomes.

Table 9: Estimates of A Unit Increase Effect on Low Birth Weight

Study	Pollution source	Pollutant	Duration	A unit increase effect on LBW
Currie and Walker (2011)	Air pollution from highway	NO_2	All gestation period	5 per 1 ppb (NO_2)
Rangel and Vogl (2019)	Agricultural Fires	PM_{10}	0–12 weeks before birth	2 per 1 $\mu g/m^3$ (PM_{10})
Alexander and Schwandt (2022)	Emissions cheating cars	PM_{10}, $PM_{2.5}$, O_3	All gestation period	44 per 1 $\mu g/m^3$ (PM_{10}), 95 per 1 $\mu g/m^3$ ($PM_{2.5}$), 48 per 1 ppb (O_3)
This study	Wildfires	PM_{10}, $PM_{2.5}$, NO_2, O_3	1 month before birth	7 per 1 $\mu g/m^3$ (PM_{10}), 6 per 1 $\mu g/m^3$ ($PM_{2.5}$), 4 per 1 ppb (NO_2), 1 per 1 ppb (O_3)

Notes: This table summarizes results in the existing literature. Currie and Walker (2011): The study shows the introduction of E-Zpass tolls decrease NO_2 by 10.8% and increase the incidence of low birth weight by 9.3 per 1,000. Rangel and Vogl (2019): The study shows that a 1 standard deviation increase in agricultural fires increase PM_{10} by 18.7 $\mu g/m^3$ on a weekly basis and decrease the incidence of low birth weight by 35 per 1,000 if the fires occur 0–12 weeks before birth continuously. Alexander and Schwandt (2022): The study shows that emissions cheating cars increase PM_{10}, $PM_{2.5}$, and O_3 by 2.2%, 2%, and 1.3% and decrease the incidence of low birth weight by 19 per 1,000. The study shows that wildfires increase PM_{10}, $PM_{2.5}$, NO_2, and O_3 by 38 $\mu g/m^3$, 43 $\mu g/m^3$, 69 ppb, and 180 ppb on a 3-day basis since wildfires occur. The same increase in wildfires decreases the incidence of low birth weight by 8.2 per 1,000. The daily pollution impact is converted to a monthly average by dividing by 30. Then, to calculate the effect of a unit increase in pollutant concentration, the effect on low birth weight is divided by the monthly average increase in pollutant concentration. The percentage effects for Currie and Walker (2011) and Alexander and Schwandt (2022) are evaluated at the average of the sample in their studies.

7 Conclusion

This is the first large scale quasi-experimental study that estimates the effects of wildfires on air pollution and pregnancy outcomes in the US. The empirical analysis uses plausibly exogenous variations in lightning strikes to identify the causal effects. The results indicate that wildfires significantly increase the concentrations of toxic pollutants, including CO, NO_2, PM_{10}, $PM_{2.5}$, O_3, and a range of VOCs. Since the impact is much larger than that

of existing studies which use HMS smoke data, the results suggest that the HMS data may underestimate the ground-level pollution caused by wildfires.

Wildfire smoke also has adverse effects on pregnancy outcomes. A 1 km^2 increase in wildfires reduces birth weight by 21.2 grams and increases the incidence of low birth weight infants by 8.2 per 1,000. The same increase in wildfires reduces gestational age by 0.1 weeks, and increases the incidence of preterm birth by 14.6 per 1,000. The results also indicate that wildfires increase the incidence of maternal diabetes by 2.0 per 1,000.

Finally, this study provides the evidence that climate change influences pregnancy outcomes through lightning-initiated wildfires. Since the amount of pollution that stems from wildfires is much larger than that stemming from traditional pollution sources, these findings indicate that the issue is shifting from man-made pollution to natural pollution due to climate change.

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A Wildfires and Health

Table A.1: Health-damaging Pollutants from Biomass Combustion from Naeher et al. (2007)

Compound	Examples	Source	Mode of toxicity
Particulate matter (PM)	*Inhalable particles* (PM_{10})	Condensation of combustion gases; incomplete combustion; entrainment of vegetation and ash fragments	Inflammation and oxidative stress, may be allergenic
	Fine particles ($PM_{2.5}$)	Condensation of combustion gases; incomplete combustion	Inflammation and oxidative stress, may be allergenic
Inorganic gases	*Carbon monoxide (CO)*	Incomplete combustion	Asphyxia
	Ozone (O_3)	Secondary reaction product of nitrogen dioxide and hydrocarbons	Irritant
	Nitrogen dioxide (NO_x)	High-temperature oxidation of nitrogen in air, some contribution from fuel nitrogen	Irritant
Hydrocarbons	*1,3-butadiene*	Incomplete combustion	Irritant, carcinogenic, mutagenic
	n-hexane		Irritant, neurotoxicity
	benzo		Mutagenic, carcinogenic
	benzene, styrene		Carcinogenic, mutagenic
Oxygenated organics	*acrolein, formaldehyde*	Incomplete combustion	Irritant, carcinogenic, mutagenic
	methanol		Irritant, teratogenic
	catechol, cresol (methylphenol)		Irritant, carcinogenic, mutagenic, teratogenic
	hydroquinone, fluorenone, anthraquinone		Irritant, allergenic, redox active, oxidative stress and inflammation, possibly carcinogenic
Chlorinated organics	*Methylene chloride, methyl chloride, dioxin*	Requires chlorine in the biomass	Central nervous system depressant (methylene chloride), possible carcinogens

B Wildfires and Pregnancy Outcomes: With Criteria Pollutants

Table B.2: Wildfires and Pregnancy Outcomes: With Criteria Pollutants, 2003-2018

	Base	PM2.5	PM10	CO	NO2	Ozone	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Birth Weight (Grams)							
Ln Wildfire Size (t - 1)	-6.345***	-6.388***	-6.332***	-6.299***	-6.339***	-6.378***	-6.374***
	(1.924)	(1.929)	(1.919)	(1.919)	(1.928)	(1.938)	(1.942)
R^2	0.653	0.653	0.653	0.654	0.653	0.653	0.653
Panel B: Low Birth Weight per 1,000							
Ln Wildfire Size (t - 1)	2.475***	2.482***	2.475***	2.488***	2.478***	2.502***	2.527***
	(0.942)	(0.944)	(0.943)	(0.943)	(0.945)	(0.951)	(0.958)
R^2	0.318	0.318	0.318	0.317	0.318	0.317	0.317
Panel C: Gestational Age (Weeks)							
Ln Wildfire Size (t - 1)	-0.034***	-0.034***	-0.034***	-0.034***	-0.034***	-0.034***	-0.034***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
R^2	0.468	0.467	0.468	0.469	0.468	0.468	0.469
Panel D: Premature per 1,000							
Ln Wildfire Size (t - 1)	4.371**	4.388**	4.356**	4.313**	4.387**	4.378**	4.351**
	(1.946)	(1.951)	(1.942)	(1.938)	(1.952)	(1.943)	(1.944)
R^2	0.323	0.323	0.324	0.325	0.323	0.323	0.324
Kleibergen-Paap F-stat.	44.1	44.1	44.0	44.0	43.9	43.6	43.2

Notes: The dependent variables are county average birth weight (grams), county total number of low birth weight infants per 1,000, county average gestational age (weeks), and county total preterm births per 1,000. Each column includes the log of each pollutants' concentration. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

C Mechanism

C.1 Heterogeneity

Table C.3: Heterogeneity: Birth Weight (IV), 2003-2018

	(1)	(2)	(3)	(4)	(5)	(6)
Ln Wildfire Size (t - 1)	-3.172*	-6.578***	-10.373**	-6.032***	-2.266	-0.376
	(1.895)	(2.017)	(4.288)	(2.078)	(2.057)	(1.533)
Ln Wildfire Size (t - 1) × Age	-5.590***					-5.403***
	(1.275)					(1.587)
Ln Wildfire Size (t - 1) × Unmarried		1.614				-0.937
		(1.339)				(2.433)
Ln Wildfire Size (t - 1) × High School or Less			-4.643			1.576
			(3.040)			(1.295)
Ln Wildfire Size (t - 1) × Black				2.517***		0.669
				(0.685)		(1.537)
Ln Wildfire Size (t - 1) × Hispanic					-5.209**	-2.236
					(2.326)	(1.926)
SW F-stat.: Ln wildfire size	41.661	37.246	14.436	46.596	72.701	69.998
SW F-stat.: Ln wildfire size × Age	52.639					107.906
SW F-stat.: Ln wildfire size × Unmarried		48.450				28.722
SW F-stat.: Ln wildfire size × High School or Less			5.473			73.284
SW F-stat.: Ln wildfire size × Black				53.240		17.159
SW F-stat.: Ln wildfire size × Hispanic					19.758	12.638
Obs.	103080	103080	90069	103080	103080	90069
R^2	0.647	0.652	0.585	0.654	0.644	0.643

Notes: The dependent variables are county average birth weight (grams). The interacted terms, age, unmarried, black, and hispanic, are maternal age, number of unmarried mothers, black mothers, and Hispanic mothers. All of these variables are standardized. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

Table C.4: Heterogeneity: Low Birth Weight (IV), 2003-2018

	(1)	(2)	(3)	(4)	(5)	(6)
Ln Wildfire Size (t - 1)	1.696*	2.620***	4.383**	2.208**	0.640	0.740
	(0.881)	(1.010)	(2.001)	(1.026)	(0.961)	(0.830)
Ln Wildfire Size (t - 1) × Age	1.327**					1.788**
	(0.553)					(0.731)
Ln Wildfire Size (t - 1) × Unmarried		0.105				2.419**
		(0.594)				(1.220)
Ln Wildfire Size (t - 1) × High School or Less			2.115			-0.943*
			(1.401)			(0.560)
Ln Wildfire Size (t - 1) × Black				-1.413***		-2.023***
				(0.319)		(0.712)
Ln Wildfire Size (t - 1) × Hispanic					2.358**	0.368
					(1.066)	(0.978)
SW F-stat.: Ln wildfire size	41.661	37.246	14.436	46.596	72.701	69.998
SW F-stat.: Ln wildfire size × Age	52.639					107.906
SW F-stat.: Ln wildfire size × Unmarried		48.450				28.722
SW F-stat.: Ln wildfire size × High School or Less			5.473			73.284
SW F-stat.: Ln wildfire size × Black				53.240		17.159
SW F-stat.: Ln wildfire size × Hispanic					19.758	12.638
Obs.	103080	103080	90069	103080	103080	90069
R^2	0.323	0.315	0.204	0.312	0.298	0.286

Notes: The dependent variable is total number of low birth weight infants per 1,000. The interacted terms, age, unmarried, black, and hispanic, are maternal age, number of unmarried mothers, black mothers, and Hispanic mothers. All of these variables are standardized. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

Table C.5: Heterogeneity: Gestational Age (IV), 2003-2018

	(1)	(2)	(3)	(4)	(5)	(6)
Ln Wildfire Size (t - 1)	-0.025**	-0.033**	-0.071**	-0.029**	-0.003	-0.003
	(0.012)	(0.013)	(0.034)	(0.014)	(0.013)	(0.013)
Ln Wildfire Size (t - 1) × Age	-0.016**					-0.015
	(0.007)					(0.009)
Ln Wildfire Size (t - 1) × Unmarried		0.011				0.003
		(0.008)				(0.016)
Ln Wildfire Size (t - 1) × High School or Less			-0.038			-0.001
			(0.026)			(0.008)
Ln Wildfire Size (t - 1) × Black				0.022***		0.014
				(0.006)		(0.010)
Ln Wildfire Size (t - 1) × Hispanic					-0.039**	-0.030*
					(0.017)	(0.015)
SW F-stat.: Ln wildfire size	41.661	37.246	14.436	46.596	72.701	69.998
SW F-stat.: Ln wildfire size × Age	52.639					107.906
SW F-stat.: Ln wildfire size × Unmarried		48.450				28.722
SW F-stat.: Ln wildfire size × High School or Less			5.473			73.284
SW F-stat.: Ln wildfire size × Black				53.240		17.159
SW F-stat.: Ln wildfire size × Hispanic					19.758	12.638
Obs.	103080	103080	90069	103080	103080	90069
R^2	0.478	0.465	0.228	0.453	0.415	0.417

Notes: The dependent variable is county average gestational age (weeks). The interacted terms, age, unmarried, black, and hispanic, are maternal age, number of unmarried mothers, black mothers, and Hispanic mothers. All of these variables are standardized. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

Table C.6: Heterogeneity: Premature (IV), 2003-2018

	(1)	(2)	(3)	(4)	(5)	(6)
Ln Wildfire Size (t - 1)	3.312*	4.561**	7.963*	3.830*	0.806	0.963
	(1.924)	(1.996)	(4.270)	(2.040)	(1.645)	(1.600)
Ln Wildfire Size (t - 1) × Age	1.796**					2.446**
	(0.804)					(1.066)
Ln Wildfire Size (t - 1) × Unmarried		-0.097				2.314
		(0.934)				(1.771)
Ln Wildfire Size (t - 1) × High School or Less			3.877			-0.810
			(3.046)			(1.072)
Ln Wildfire Size (t - 1) × Black				-2.507***		-2.422**
				(0.791)		(1.230)
Ln Wildfire Size (t - 1) × Hispanic					4.520**	2.227
					(2.278)	(1.935)
SW F-stat.: Ln wildfire size	41.661	37.246	14.436	46.596	72.701	69.998
SW F-stat.: Ln wildfire size × Age	52.639					107.906
SW F-stat.: Ln wildfire size × Unmarried		48.450				28.722
SW F-stat.: Ln wildfire size × High School or Less			5.473			73.284
SW F-stat.: Ln wildfire size × Black				53.240		17.159
SW F-stat.: Ln wildfire size × Hispanic					19.758	12.638
Obs.	103080	103080	90069	103080	103080	90069
R^2	0.335	0.321	0.118	0.312	0.276	0.297

Notes: The dependent variable is county total preterm births per 1,000. The interacted terms, age, unmarried, black, and hispanic, are maternal age, number of unmarried mothers, black mothers, and Hispanic mothers. All of these variables are standardized. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

C.2 Without Large Fires

Table C.7: No Large Fires ($< 10\text{km}^2$) (IV), 2003-2018

	Birth Weight (Grams)	Low Birth Weight per 1,000	Gestational Age (Weeks)	Premature per 1,000
	(1)	(2)	(3)	(4)
Ln Wildfire Size (t - 1)	-7.258***	3.178***	-0.040***	5.307**
	(2.311)	(1.138)	(0.015)	(2.364)
County FE	X	X	X	X
Year-Month FE	X	X	X	X
Fire Weather Controls	X	X	X	X
Kleibergen-Paap F-stat.	49.2	49.2	49.2	49.2
Counties	576	576	576	576
Obs.	101619	101619	101619	101619
R^2	0.647	0.302	0.454	0.303

Notes: The dependent variables are county average birth weight (grams), county total number of low birth weight infants per 1,000, county average gestational age (weeks), and county total preterm births per 1,000. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

D Placebo Tests: No Wildfire Sample

Table D.8: Placebo Tests: No Wildfire Sample

	Birth Weight (1)	Low Birth Weight (2)	Gestational Age (3)	Premature (4)
Std. Lightning Count (t - 1)	-0.187	0.023	0.001	0.027
	(0.460)	(0.218)	(0.002)	(0.295)
County FE	X	X	X	X
Year-Month FE	X	X	X	X
Fire Weather Controls	X	X	X	X
Counties	555	555	555	555
Obs.	33036	33036	33036	33036
R^2	0.645	0.313	0.471	0.315

Notes: Columns 1 and 2 are the OLS estimates and Columns 3 and 4 are TWFE-robust estimates based on Borusyak et al. (2022). The observational unit is at the county-month level. All estimations include all weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

E TWFE Robust Estimator

Table E.1: Wildfires and Pregnancy Outcomes: TWFE Robust, 2003-2018

	TWFE		BJS	
	Reduced (1)	Wald (2)	Reduced (3)	Wald (4)
Birth Weight (Grams)				
1[Lightning ≥ 10000]	-2.555***	-8.363	-2.944***	-6.581
	(0.694)		(0.726)	
Low Birth Weight per 1,000				
1[Lightning ≥ 10000]	1.048***	3.429	1.141***	2.551
	(0.340)		(0.369)	
Gestational Age (Weeks)				
1[Lightning ≥ 10000]	-0.016***	-0.052	-0.018***	-0.040
	(0.004)		(0.004)	
Premature per 1,000				
1[Lightning ≥ 10000]	2.255***	7.382	2.157***	4.821
	(0.566)		(0.534)	
First-stage				
1[Lightning ≥ 10000]	0.305***		0.447***	
	(0.043)		(0.047)	
Fire Weather Controls	X		X	
Other Weather Controls	X		X	
County FE	X		X	
Year-Month FE	X		X	
Obs.	103080		103080	

Notes: Columns 1 and 2 are the OLS estimates and Columns 3 and 4 are TWFE-robust estimates by Borusyak et al. (2022). The observational unit is at the county-month level. All estimations include all weather controls, county fixed effects, and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

F Robustness Checks for Log with Zeros

Table F.1: Robustness Checks for Log with Zeros (IV), 2003-2018

	Base	x = 0	x = 0.1	x = 1	x = 3	x = 5
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Birth Weight (Grams)						
Ln Wildfire Size (t - 1)	-6.345***	-5.345***	-5.339***	-5.293***	-5.193***	-5.097***
	(1.924)	(1.877)	(1.879)	(1.895)	(1.931)	(1.969)
R^2	0.653	0.576	0.575	0.564	0.538	0.510
Panel B: Low Birth Weight per 1,000						
Ln Wildfire Size (t - 1)	2.475***	2.085**	2.083**	2.065**	2.026**	1.988**
	(0.942)	(0.889)	(0.889)	(0.893)	(0.901)	(0.911)
R^2	0.318	0.217	0.216	0.201	0.168	0.131
Panel C: Gestational Age (Weeks)						
Ln Wildfire Size (t - 1)	-0.034***	-0.029**	-0.029**	-0.029**	-0.028**	-0.028**
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
R^2	0.468	0.325	0.323	0.302	0.254	0.202
Panel D: Premature per 1,000						
Ln Wildfire Size (t - 1)	4.371**	3.682**	3.678**	3.647**	3.578**	3.512**
	(1.946)	(1.758)	(1.758)	(1.759)	(1.762)	(1.767)
R^2	0.323	0.147	0.144	0.119	0.060	-0.004
Kleibergen-Paap F-stat.	44.1	18.1	17.9	16.6	14.2	12.2

Notes: Ln Wildfire Size is a log of wildfire size divided by the minimum wildfire size in the sample, using $-x$ if the wildfire size is zero. The dependent variables are county average birth weight (grams), county total number of low birth weight infants per 1,000, county average gestational age (weeks), and county total preterm births per 1,000. The observational unit is at the county-month level. All estimations include fire weather controls, other weather controls, county fixed effects and year-month fixed effects. Standard errors clustered by county are shown in parentheses.

G Robustness Checks for Spatial Correlation

Table G.1: Robustness Checks for Spatial Correlation (IV), 2003-2018

	Grams	LBW	Weeks	Premature
	(1)	(2)	(3)	(4)
Ln Wildfire Size (t - 1)	-6.345***	2.475**	-0.034**	4.371**
	(2.210)	(1.079)	(0.014)	(2.123)
County FE	X	X	X	X
Year-Month FE	X	X	X	X
Fire Weather Controls	X	X	X	X
First-Stage F-stat.	21.1	21.1	21.1	21.1
Counties	576	576	576	576
Obs.	103080	103080	103080	103080
R^2	0.653	0.318	0.468	0.323

Notes: The dependent variables are county average birth weight (grams), county total number of low birth weight infants per 1,000, county average gestational age (weeks), and county total preterm births per 1,000. The observational unit is at the county-month level. All estimations include fire weather controls, county fixed effects and year-month fixed effects. Standard errors calculated using Conley standard errors, using 100km as the threshold, are shown in parentheses.