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 standard deviation 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 118.1 grams and decreases gestational age by 0.377 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). 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 measurement error of wildfires. A growing body of literature uses wildfire smoke data detected by satellite imagery, which may not accurately measure invisible gaseous pollutants.(e.g., Chen et al., 2021; Borgschulte et al., 2022; Molitor et al., 2023)[2]

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

[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.

[2] Borgschulte et al. (2022) conclude that particulate matter is the signature emission of wildfires in comparison with other pollutants, such as CO and NO_2. Therefore, wildfire smoke are used as an instrument for $PM_{2.5}$.

instrumental variable (IV) for wildfires. This study also uses wildfire data obtained from the United States Forest Service (USFS), which reports fire size at the incident level, regardless of the pollutants emitted.

This IV approach is also motivated by the fact that a common quasi-experimental design in pollution studies use wind patterns as exogenous variation, which may explain limited variation in pollution (e.g., Sheldon and Sankaran, 2017; Rangel and Vogl, 2019; He et al., 2020). As various pollutants are emitted into the air, each pollutant may have different dispersion properties. For example, wind patterns mainly explain the variation in particulate pollutants (e.g., $PM_{2.5}$, PM_{10}), not gaseous pollutants (e.g., CO, O_3, NO_2, VOCs) (Rangel and Vogl, 2019; He et al., 2020). As a result, estimations using wind patterns may not fully capture the health effects of pollution sources.

This study has two key findings. First, wildfires cause considerable air pollution. A 1 standard deviation increase in wildfires (i.e., 3.4 km^2) emits various pollutants well above the national air quality standards at the county average. In addition to criteria air pollutants, wildfire smoke contains many other toxic pollutants, such as 1,3-butadiene and benzene. In contrast to previous wildfire studies, the rigorous specifications demonstrate that the pollution from wildfire smoke is considerably larger than man-made pollution. Compared with the findings of Currie and Walker (2011), the NO_2 concentration from a 1 standard deviation increase in wildfire *at the county level* is approximately eight times higher than the concentration from traffic congestion *within 2 km of a toll plaza*.

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 standard deviation increase in monthly wildfires reduces birth weight by 118.1 grams and increases the number of low birth weight infants by 37.17 per 1,000 at the county level. The same increase in wildfires also reduces gestational age by 0.377 weeks and increases the number of preterm births by 69.93 per 1,000. In comparison with Currie and Walker (2011), the impact of the same increase in wildfire *at the county level* are approximately four times and eight times larger than the impact of traffic congestion *within 2 km of a toll plaza* on low birth weight and preterm births, respectively.

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.[3] Since existing 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.[4] 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. The IV strategy thus addresses the endogeneity of wildfires and provides more rigorous evidence on the adverse health effects of wildfire smoke. Given that many wildfires are the result of human activities, concerns about economic confounders may also apply to existing studies on wildfires and health (e.g., Chen et al., 2021; Borgschulte et al., 2022; Heft-Neal et al., 2022; Molitor et al., 2023). Moreover, in contrast to the existing literature, this study reveals that wildfires emit a significant amount of gaseous pollutants. The results indicate that prior work using wildfire smoke data from satellite data may not accurately identify the impact of invisible gaseous pollutants. This study therefore provides insight into the impact of wildfires on pollution and health.

Third, the novel IV strategy enables the results to be compared with those using wind patterns for identification. For comparison, this study replicates the results using the identification strategy from Rangel and Vogl (2019) and He et al. (2020). The replicated results indicate that the estimates are much smaller, especially for gaseous pollutants. The difference in results may be because wind patterns only partially explain the variation in pollution and underestimate its adverse effects. In addition to the pollu-

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

tion analysis, the replicated estimations do not find adverse health effects. Thus, existing pollution studies using wind patterns should be interpreted with caution because they may only capture the effect through a subset of pollutants (e.g., Schlenker and Walker, 2016; Anderson, 2020; Bondy et al., 2020).

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.

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 previous 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.

[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

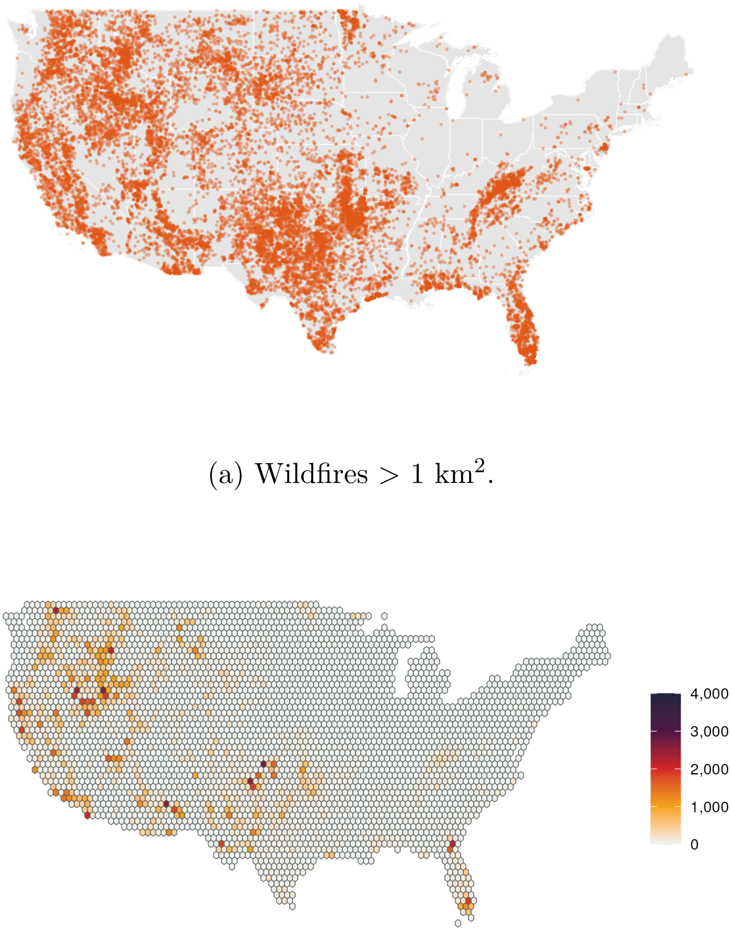
Table 1: Summary Statistics: Wildfire Size (km^2) by Cause (2003–2018)

	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	107,717	0.2	8.5	1,660.0	26,027.8
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	366,498	0.2	10.0	2,681.9	86,781.3
Misuse of fire by a minor	31,687	0.0	1.3	155.2	1,089.0
Natural (including lightning)	174,133	1.1	19.0	2,258.9	188,648.3
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	1,296,297	0.3	9.6	2,681.9	372,939.9

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).

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. 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 $1km^2$ and (b) the distribution of the total burned area. Figure 1 (a) and (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.



(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.

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 quantile 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.

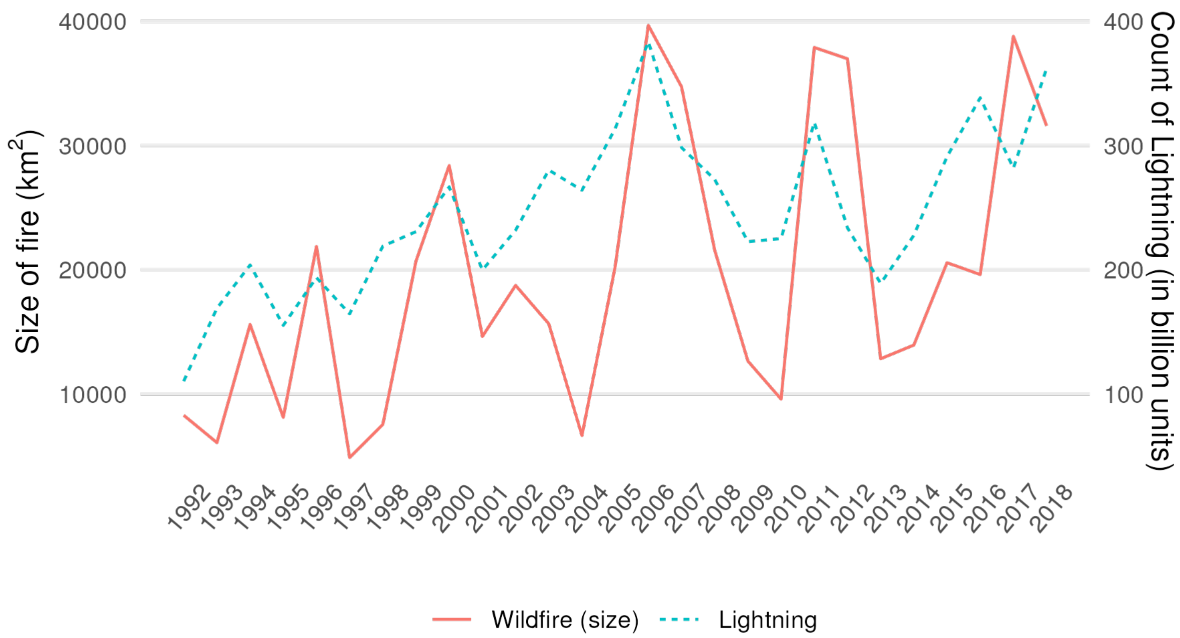


Figure 2: Annual Trends of Wildfires and Lightning Strikes.

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}, $PM_{2.5}$.[7] 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.

Wildfires also emit inorganic gases, such as CO and NO_x[8] 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

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

[8] 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.[9] 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.[10] 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

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

[10] 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.

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.[11] 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.[12] 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.[13] 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

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

[12] 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).

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

for pollutants regulated under the Clean Air Act[14]. A variety of pollutants are used in this study (the number of counties available in the data is shown in parentheses): PM_{10} (594), $PM_{2.5}$ (831), CO (298), O_3 (909), NO_2 (373), and numerous VOCs (1,3-butadiene (859), benzene (965), styrene (905), n-hexane (616), and non-methane VOCs (NMVOCs) (406)).[15] 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.[16] The units of measurement for the standards are parts per billion (ppb), parts per million (ppm), and micrograms per cubic meter (μg/m^3). The standards for PM_{10} and $PM_{2.5}$ are 150μg/m^3 and 35μg/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.[17] 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 birth. For pregnancy outcomes, this study uses the county average birth weight and

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

[15] 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.

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

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

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 with agricultural income effects that affect human health (Rangel and Vogl, 2019; He

Table 2: Summary Statistics

	Obs.	Mean	S.D.	Min	10th %	90th %	Max
Panel A. Wildfires and pollution							
Wildfire size (km^2)	18,160,044	0.0	3.5	0.0	0.0	0.0	3,673.2
Number of Wildfires	18,160,044	0.3	1.0	0.0	0.0	1.0	129.0
Number of Lightning	18,160,044	90.1	483.1	0.0	0.0	108.0	54,572.0
CO (ppm)	1,062,609	0.4	0.3	0.0	0.1	0.7	5.0
NO_2 (ppb)	1,334,983	9.2	7.5	0.0	1.7	19.3	179.4
PM_{10}($\mu g/m^3$)	1,187,747	21.0	24.2	0.2	7.0	38.0	10,020.0
$PM_{2.5}$($\mu g/m^3$)	1,824,927	9.6	6.8	0.0	3.4	17.4	411.7
O_3 (ppb)	3,555,742	32.0	11.7	0.0	17.2	47.3	109.5
1,3-Butadiene (ppb)	352,876	0.3	1.3	0.0	0.0	0.6	128.0
Benzene (ppb)	746,912	1.6	10.8	0.0	0.4	2.9	9,051.1
Styrene (ppb)	543,776	0.5	4.1	0.0	0.0	0.8	995.0
n-Hexane (ppb)	565,828	1.5	12.1	0.0	0.2	3.1	8,716.8
NMVOC (ppb)	552,252	123.9	185.6	0.0	23.7	236.4	9,080.0
Panel B. Wildfires and health							
Wildfire size (km^2)	671,328	1.2	21.2	0.0	0.0	0.7	3,686.7
Num. of Lightning	671,328	2,663.2	4,639.3	0.0	0.0	8,128.0	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.

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)[18] 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)[19] has implemented preventive measures for California's wildlands while maintaining the quality of California ecosystems.[20] 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 be underestimated.

4.2 Instrumental Variable Estimation

The baseline specification for estimating the effects of wildfires on pollution and health as follows:

$$Y_{it} = \beta \ln Wildfire_{it} + X_{it}\gamma + \delta_i + \zeta_t + \varepsilon_{it}, \tag{1}$$

where the dependent variable is the outcome of interest in county i in period t (Y_{it}). This study has two key outcomes. The first outcome is a variety of pollutants. The pollutants used in this study are CO, NO_2, PM_{10}, $PM_{2.5}$, O_3, and a variety of VOCs. The second outcome is pregnancy outcome, which includes birth weight and gestational

[18]Fire weather and climate, NICC: https://www.predictiveservices.nifc.gov/weather/weather.htm
[19]CAL FIRE: https://wildfiretaskforce.org
[20]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.

age. The parameter of interest is β, which is the coefficient of a logarithm of wildfire size ($\ln Wildfire_{it}$). To avoid missing values, this study adds 0.001 to the wildfire size before taking the logarithm.

Eq.(1) includes county fixed effects (δ_i) and time fixed effects (ζ_t). 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 time fixed effects indicate day-month-year fixed effects for the pollution analysis and month-year fixed effects for the health analysis. These 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.(1) are prone to bias due to the identification concerns described above. Therefore, this study employs a novel IV strategy involving the use of lightning as an instrument for wildfires.[21] The specification for the first stage is as follows:

$$\ln Wildfire_{it} = \alpha Lightning_{it} + X_{it}\lambda + \nu_i + \xi_t + \upsilon_{it}, \tag{2}$$

where $Lightning_{it}$ is the number of lightning strikes in county i and period t. The remaining notation is the same as that described in Eq.(1).[22]

The vector X_{it} includes fire weather conditions (i.e., humidity, precipitation, temperature, and a set of all possible interactions among them).[23] Lightning-initiated wildfires are caused by lightning strikes in the absence of rainfall. Therefore, to capture the variation among all lightning incidents, the fire weather variables are controlled. The other weather variables (i.e., air pressure, wind direction, and wind speed) are included to check for weather-related confounders.

[21]This study does not use natural-caused wildfires as an exogenous variable because the wildfire database may be subject to measurement error. For example, the causes of approximately 0.4 million wildfires of the 1.3 million wildfires are unspecified.

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

[23]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.

Using lightning strikes as an instrument allows β to capture the effects of lightning-initiated wildfires separately from human-caused wildfires. Therefore, the IV estimations eliminate the endogeneity issues caused by human-caused wildfires. In addition, lightning strikes occur everywhere, even in remote areas that are difficult for firefighters to access. Table 1 shows that the average size and the standard deviation of natural-caused wildfires are significantly larger than those of all other fires. Moreover, lightning travels many miles randomly through the air and strikes only one spot on the ground, making lightning strikes difficult to predict and prepare for in advance. Because lightning-initiated wildfires are difficult to suppress, these fires are not confounded by fire management responses.

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., 474) increases the burned area by 1.792%. 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 0.021. 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 are 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. This indicates 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 are more pronounced due to climate warming. Therefore, climate change significantly influences wildfires through lightning strikes during extreme weather.

Table 3: Lightning Strikes and Wildfires

	Size (km^2)			Count		
	(1)	(2)	(3)	(4)	(5)	(6)
Std. Num. of Lightning	0.018	0.018	-0.004	0.021	0.021	0.025
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Std. Num. of Lightning × Std. Temp.			0.099			0.096
			(0.006)			(0.017)
Std. Num. of Lightning × Std. Precip.			0.000			0.000
			(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.)	-6.603	-6.603	-6.603	0.255	0.255	0.255
SD (Dep. var.)	1.039	1.039	1.039	1.000	1.000	1.000
Counties	3108	3108	3108	3108	3108	3108
Obs.	19294464	19294464	19294464	19294464	19294464	19294464
R^2	0.170	0.171	0.171	0.184	0.184	0.185

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. 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.

All wildfire coefficients are positive and statistically significant. At the average of the sample[24], the causal effects of a 1 standard deviation increase in wildfires (i.e., 3.4 km^2) are 2,375% for CO, 7,828% for NO_2, 843% for PM_{10}, 4,574% for $PM_{2.5}$, and 5,411% for O_3.

[24]Since the wildfire is a logarithmic variable, the impact of wildfires on pollution is calculated based on the average size of wildfire on a daily basis (i.e., 0.04 km). Therefore, the impact of a 1 standard deviation increase in wildfires (3.4 km^2) is calculated by $\beta \times \frac{3.4}{0.04}$.

The impact significantly exceed those outlined by EPA standards at the average of the sample. In addition, VOCs are also emitted by wildfires, and the effects are statistically significant. A 1 standard deviation increase in wildfire burning emits 1,3-butadiene by 4,634%, benzene by 6,788%, styrene by 2,713%, n-hexane by 12,793%, and NMVOCs by 14,304%, thus exceeding the ninetieth percentile of the distribution excluding NMVOCs.

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.[25] 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.

Appendix Figure C.1 also shows the event study results of wildfires on pollution, using lagged and leading wildfire variables.[26] 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.

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

	Particulate Pollutants		Gaseous Pollutants							
	PM_{10} (1)	$PM_{2.5}$ (2)	CO (3)	NO_2 (4)	O_3 (5)	1,3-Butadiene (6)	Benzen (7)	Styrene (8)	n-Hexane (9)	NMVOC (10)
Ln Wildfire Size	0.098	0.532	0.276	0.910	0.629	0.539	0.789	0.316	1.488	1.664
	(0.034)	(0.060)	(0.061)	(0.114)	(0.072)	(0.123)	(0.116)	(0.159)	(0.282)	(0.469)
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.	70.168	88.574	27.768	39.579	76.404	18.175	42.804	34.998	30.094	11.743
Mean (Dep. var.)	2.817	2.050	-1.243	1.837	3.386	-1.848	0.079	-1.862	-0.190	4.353
SD (Dep. var.)	0.684	0.681	0.813	0.997	0.441	1.089	0.856	1.417	1.083	0.994
Counties	594	831	298	373	909	859	965	905	616	406
Obs.	1187747	1824927	1062609	1334983	3555742	352876	746912	543776	565828	552252

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.

[25] 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.

[26] For almost all instruments, the first-stage F-statistics by Sanderson and Windmeijer (2016) are above 10.

5.3 Wildfires and Health

Table 5 estimates the effects of wildfires on pregnancy outcomes, using county-month-level panel data. 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 sample[27], a 1 standard deviation increase in wildfires (i.e., 21.2 km^2) is associated with an increase of 2.345 grams in birth weight. The same increase in wildfires is associated with a decrease in the gestational age of 0.016 weeks.[28]

Table 5: 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 (1)	IV (2)	IV (3)	IV (4)	OLS (5)	IV (6)	IV (7)	IV (8)
Ln Wildfire Size	0.094	-4.875	-4.750	1.495	-0.001	-0.015	-0.015	2.814
	(0.083)	(1.852)	(1.904)	(0.788)	(0.000)	(0.012)	(0.012)	(1.699)
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.		35.752	34.678	34.678		34.678	34.678	34.678
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	0.673	0.661	0.662	0.334	0.504	0.497	0.497	0.350

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 standard deviation increase in wildfires reduces birth weight by 118.1 grams at the average of the wildfires. In addition, the same increase in the size of wildfires reduces the gestation period by

[27] Since the wildfire is a logarithmic variable, the impact of wildfires on pregnancy outcomes is calculated based on the average size of wildfire on a monthly basis (i.e., 1.2 km^2). Therefore, the impact of a 1 standard deviation increase in wildfires (21.2 km^2) is calculated by $\beta \times \frac{21.2}{1.2}$.

[28] Approximately 0.83 million infants experienced at least a 1 standard deviation increase in wildfires in the month of birth from 2003 to 2018.

0.377 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 5 report the effects of wildfires on the number of low birth weight infants (below 2500 grams) and preterm (below 38 weeks) births. A 1 standard deviation increase in wildfires increases the incidence of low birth weight by 37.17 per 1,000 and the incidence of preterm birth by 69.93 per 1,000.

Lagged effects.

Table 6 reports estimates of the lagged effects of wildfire on pregnancy outcomes. The specifications include lagged effects every 3 months, with a maximum of 9 months of in utero wildfire exposure to account for the average gestational age in the US (i.e., 38.6 weeks). Column 5 in Table 6 provides first-stage F-statistics for all instrumental variables. This study uses conditional Sanderson and Windmeijer (2016) first-stage F-statistics, which are used as test statistics for weak instruments in a model with multiple endogenous variables. These statistics confirm the relevance of the instrument across specifications.

The patterns in Table 6 reveal that the largest effects are for month of birth. Thereafter, the effects decrease for earlier gestation periods. Wildfires 6 months prior to birth are positively associated with average birth weight, number of low birth weight infants, and average gestational age. In this study, the point estimates of lagged wildfires may be biased due to selection from prematurity.[29] Moreover, wildfire exposure in the month of pregnancy has negative effects on birth weight and gestational age.

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

[29]These results are consistent with those of Rangel and Vogl (2019), who showed that agricultural fires 13–25 weeks before birth have positive effects on birth weight. In contrast, such fires 0–12 weeks and 26–38 weeks before birth have negative effects on birth weight.

Table 6: Wildfires and Pregnancy Outcomes: Lagged Effects, 2003-2018

	Birth Weight		Gestational Age		
	Grams (1)	LBW (2)	Weeks (3)	Premature (4)	SW F-stat. (5)
Ln Wildfire Size	-5.756	-0.486	-0.033	5.000	17.558
	(4.365)	(1.916)	(0.041)	(5.935)	
Ln Wildfire Size on Months 3 Before Birth	-4.054	-0.770	-0.056	2.966	34.209
	(4.363)	(1.888)	(0.041)	(5.796)	
Ln Wildfire Size on Months 6 Before Birth	1.108	-3.969	-0.028	2.241	13.313
	(4.757)	(2.285)	(0.039)	(5.555)	
Ln Wildfire Size on Months 9 Before Birth	-2.993	-1.046	-0.011	1.814	46.356
	(2.972)	(1.469)	(0.020)	(2.775)	
County FE	X	X	X	X	
Year-Month FE	X	X	X	X	
Fire Weather Controls	X	X	X	X	
Mean (Dep. Var.)	3279.471	78.304	38.628	116.910	
SD (Dep. Var.)	76.443	26.131	0.302	34.819	
Counties	576	576	576	576	
Obs.	103080	103080	103080	103080	
R^2	0.642	0.265	0.322	0.256	

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.

Vogl, 2019). At the sample mean of wildfires and births, a 1 standard deviation increase in wildfires reduces the number of live births by approximately 0.856.

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 standard deviation increase in wildfires increases the number of mortality within the 1st day by 0.394 and the 1st year by 0.05, although the standard errors are large.

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 standard deviation increase in wildfires decreases pregnancy-associated hypertension by 7.56 and increases eclampsia by 8.611 per 1,000. However, these point estimates are small and not statistically significant at the conventional level.

In contrast, the same increase in wildfires significantly increases diabetes by 69.42 per 1,000. A systematic review by Yang et al. (2020) show that air pollutants are as-

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	-0.034	0.016	0.002	-0.304	2.793	0.346
	(0.009)	(0.025)	(0.002)	(0.992)	(1.006)	(0.479)
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.	35.752	91.069	92.890	39.780	38.608	32.687
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	0.778	0.653	0.039	0.450	0.435	0.174

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.

sociated 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

[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.

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 D.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 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.(1) as endogenous variables, and the interactions between lightning strikes and maternal characteristics are added to Eq.(2) as instruments.

Appendix Table D.3 to D.6 reports the results for heterogeneous effects of wildfires on pregnancy outcomes. Focusing on column 6 in all tables, this study finds no significant differences for single, less educated, black, and Hispanic mothers. One exception is that, the effect of wildfires on birth weight is larger for older mothers. The results therefore differ from the existing literature on the mental health effects of natural disasters. Overall, the heterogeneous effects of wildfires on pregnancy outcomes are not consistent with the existing literature on the mental health effects of natural disasters, suggesting that the mechanism of the effects of wildfires on pregnancy outcomes is mainly through air pollution.

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.

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

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 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 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	-4.750	-5.210	-4.620	-4.310	-5.696	-4.388
	(1.904)	(1.960)	(1.814)	(2.341)	(2.367)	(1.801)
R^2	0.662	0.667	0.688	0.671	0.657	0.675
Panel B: Low Birth Weight per 1,000						
Ln Wildfire Size	1.495	1.764	1.410	0.855	1.922	1.460
	(0.788)	(0.808)	(0.762)	(1.066)	(0.972)	(0.777)
R^2	0.334	0.335	0.392	0.353	0.328	0.350
Panel C: Gestational Age (Weeks)						
Ln Wildfire Size	-0.015	-0.016	-0.014	-0.022	-0.018	-0.014
	(0.012)	(0.012)	(0.012)	(0.015)	(0.015)	(0.010)
R^2	0.497	0.502	0.519	0.501	0.495	0.524
Panel D: Premature per 1,000						
Ln Wildfire Size	2.814	3.194	2.824	3.718	3.562	2.602
	(1.699)	(1.748)	(1.714)	(2.184)	(2.113)	(1.395)
Kleibergen-Paap F-stat.	35.752	35.808	35.182	65.976	27.634	37.161
R^2	0.350	0.350	0.381	0.353	0.340	0.381

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

[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 precipitation from satellite data.

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 F.10 reports that a 1 standard deviation increase in lightning strikes is associated with a decrease of 0.272 grams for birth weight, an increase of 0.168 per 1,000 for the number of low birth weight infants, a decrease of 0 weeks for gestational age, and an increase of 0.403 per 1,000 for the number of preterm births. 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 G.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

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

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 H.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 I.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

Comparison with other sources of pollution.

Many economic studies show that man-made air pollution has adverse effects on health at birth. For example, Currie and Walker (2011) show that the traffic congestion increases NO_2 by 10.8% *within 2 km of toll plaza.* Currie et al. (2015) also show that toxic industrial plants release approximately 1 and 0 standard deviations of benzene and styrene, respectively, *at 0.5 miles from a plant*, respectively. In contrast, this study shows that a 1 standard deviation increase wildfire raises *the county average* NO_2 concentration by 7,828%. The same increase in wildfire also raises a 10.2 and 3.2 standard deviations of benzene and styrene at the average of the sample, respectively.

Regarding the effects on health at birth, Currie and Walker (2011) show that traffic congestion increases the occurrence of low birth weight infants and preterm birth by 8.6 and 9.3 per 1,000, respectively *within 2 km of a toll plaza.* Currie et al. (2015) also show that toxic industrial plant release increases low birth weight by 30 per 1,000 *within 1 mile of the plant.* In contrast, this study shows that a 1 standard deviation wildfire increases low birth weight and preterm birth by 37.17 and 69.93 per 1,000 *at county level*.

The comparison suggests that the wildfires temporarily cause more severe air pollution than pollution from traffic congestion and toxic industrial plants. Accordingly, the acute health damages from wildfires are significantly larger than the chronic health damages from man-made pollution. In addition, the impact of wildfires are not limited to the vicinity of the source, but spread over a wide area.

Comparison with the evidence from wind direction.

The IV results differ from existing natural experimental studies using wind direction.[34] The difference in the results may be due to the different dispersion properties of the pollutants by wind and may underestimate the impact of wildfires on pollution. To compare the results, this study replicates the estimation using wind direction based on Rangel and Vogl (2019) and He et al. (2020). The methodology and results are reported in Appendix E.

Table E.8 shows that wildfires have significant impact on all air pollutants (see Wald estimates in Table E.8). However, the impact is significantly smaller than the impact of wildfires shown in Table 4. The impact on particulate pollutants (i.e., PM_{10}, $PM_{2.5}$) is 16% and 3.9% of those estimated using lightning strikes, respectively. In addition, the estimates on gaseous pollutants are less than 4% of the estimates by lightning strikes. These results are similar to Rangel and Vogl (2019) and He et al. (2020), which show that wind direction explains particulate pollutants but not gaseous pollutants.

Table E.9 show the impact of upwind and downwind fires on pregnancy outcomes. The results do not reveal adverse effects of wildfires on either birth weight or gestational age (see Wald estimates in Table E.9). This suggests that as the impact of wildfires on pollution is underestimated, their effect on pregnancy outcomes is also underestimated. The results are also not driven by attenuation bias due to classical measurement error,

[34] Rangel and Vogl (2019) shows that agricultural fires increase PM_{10} and O_3, but does not increase NO_x He et al. (2020) shows that straw burning increases PM_{10} and $PM_{2.5}$ but does not increase SO_2 and NO_2. In contrast, this study reveals that wildfires significantly increase the concentrations of CO, NO_2, PM_{10}, $PM_{2.5}$, O_3, and a variety of VOCs.

as some estimates are of unexpected sign.[35]

One concern related to these interpretations is that the IV strategy using lightning strikes may have a LATE interpretation that captures the impact of larger wildfires rather than of other fires (see Table 1). However, as shown in Figure E.2, this study does not find any trend in the impact of wildfires on pollution with respect to the size of fires. Similarly, Figure E.3 shows that the impact of wildfires on birth weight and gestational age is not dependent on the size of fires.

Overall, wind direction mainly explains particulate pollutants (e.g., PM_{10}, $PM_{2.5}$) but not gaseous pollutants (e.g., CO, NO_2, O_3). In addition, even the impact on particulate pollutants is smaller than the impact estimated by lightning strikes. The results imply that the identification strategy using wind patterns cannot fully capture the impact of the pollution. Therefore, the findings caution against pollution studies that rely on wind direction as an exogenous variation (e.g., Schlenker and Walker, 2016; Anderson, 2020; Bondy et al., 2020)

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. The impact is significantly larger than those of man-made pollution found in existing studies.

Wildfire smoke also has adverse effects on pregnancy outcomes. A 1 standard deviation increase in wildfires reduces birth weight by 118.1 grams and increases the incidence of low birth weight infants by 37.17 per 1,000. The same increase in wildfires reduces gestational age by 0.377 weeks, and increases the incidence of preterm birth by 69.93 per 1,000. The results also indicate that wildfires increase the incidence of maternal diabetes

[35] Under two assumptions: (1) classical measurement errors with the same variance and (2) the same variance of upwind fires and downwind fires are assumed, the estimates of upwind fires and downwind fires have the same rate of attenuation bias.

by 69.42 per 1,000. The impact is significantly larger than other sources of pollution, such as traffic congestion and toxic industrial plants. The impact of pollution is also not limited to the vicinity of the source.

In addition, this study compares the results with the existing strategy using wind direction. To compare the results, this study replicates the estimation using wind direction based on Rangel and Vogl (2019) and He et al. (2020). The results show that while wildfires increase particulate pollutants, the impact are negligible for gaseous pollutants. In addition, this study does not reveal an impact on pregnancy outcomes. The results indicate that the wind direction strategy depends on the dispersion properties of pollutants and may fail to estimate the impact of pollution. This comparison warns the literature on pollution against using wind patterns since this approach may underestimate the adverse effects of pollution. The IV strategy using lightning strikes is thus proposed as a solution to this problem.

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

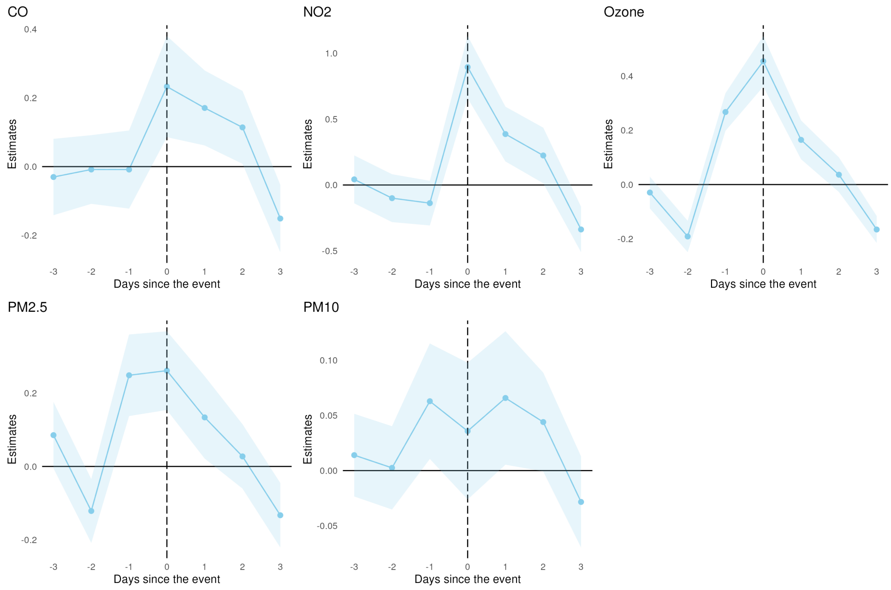
B Wildfires and Pregnancy Outcomes: With Criteria Pollutants

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

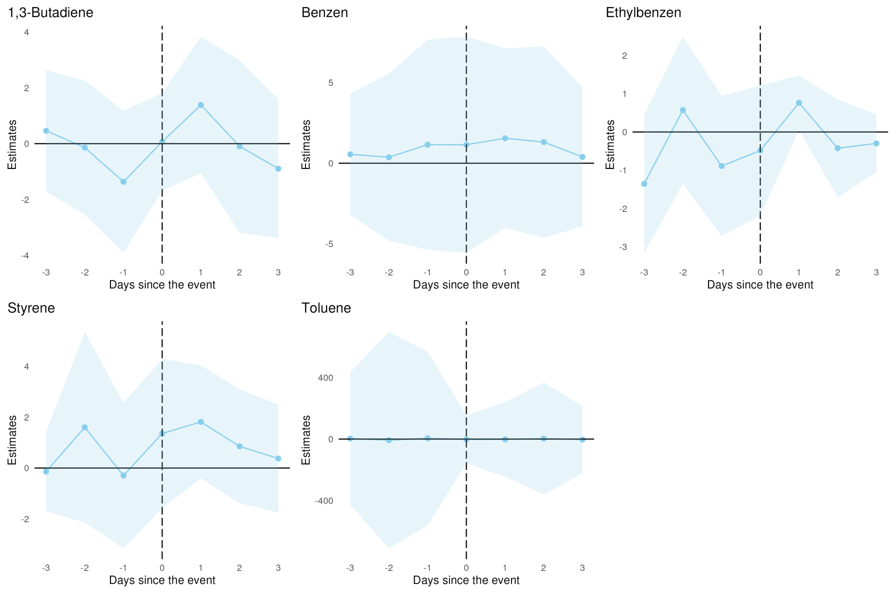
	Base model	$PM_{2.5}$	PM_{10}	CO	NO_2	O_3	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Birth Weight (Grams)							
Ln Wildfire Size	-4.750	-4.564	-4.772	-4.753	-4.735	-4.689	-4.504
	(1.904)	(1.880)	(1.911)	(1.903)	(1.904)	(1.903)	(1.884)
R^2	0.662	0.663	0.661	0.662	0.662	0.662	0.663
Panel B: Low Birth Weight per 1,000							
Ln Wildfire Size	1.495	1.447	1.514	1.498	1.492	1.485	1.447
	(0.788)	(0.782)	(0.790)	(0.788)	(0.788)	(0.791)	(0.788)
R^2	0.334	0.334	0.333	0.334	0.334	0.334	0.334
Panel C: Gestational Age (Weeks)							
Ln Wildfire Size	-0.015	-0.014	-0.015	-0.015	-0.015	-0.015	-0.014
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
R^2	0.497	0.498	0.498	0.497	0.497	0.497	0.499
Panel D: Premature per 1,000							
Ln Wildfire Size	2.814	2.770	2.829	2.812	2.819	2.784	2.756
	(1.699)	(1.699)	(1.703)	(1.698)	(1.699)	(1.695)	(1.699)
Kleibergen-Paap F-stat.	34.678	34.871	34.543	34.671	34.666	34.614	34.662
R^2	0.350	0.351	0.350	0.350	0.350	0.351	0.351

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 Wildfires and Polluiton: Event Study



(a) Criteria Pollutants



(b) Volatile Organic Compounds (VOCs)

Figure C.1: Wildfires and Pollution: Event Study (IV), 2003-2018

D Mechanism

D.1 Heterogeneity

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

	(1)	(2)	(3)	(4)	(5)	(6)
Ln Wildfire Size	-2.788	-5.674	-5.940	-5.345	-2.431	-0.933
	(1.870)	(1.653)	(3.134)	(2.013)	(1.680)	(1.263)
Ln Wildfire Size × Age	-5.990					-4.016
	(1.284)					(1.516)
Ln Wildfire Size × Unmarried		2.875				1.631
		(1.445)				(2.674)
Ln Wildfire Size × High School or Less			-2.262			1.700
			(2.404)			(1.226)
Ln Wildfire Size × Black				1.996		-0.760
				(0.651)		(1.650)
Ln Wildfire Size × Hispanic					-3.987	-1.535
					(2.347)	(2.111)
SW F-stat.: Ln wildfire size	34.160	31.574	12.690	37.616	54.959	14.719
SW F-stat.: Ln wildfire size × Age	53.734					94.971
SW F-stat.: Ln wildfire size × Unmarried		51.771				17.625
SW F-stat.: Ln wildfire size × High School or Less			5.714			68.990
SW F-stat.: Ln wildfire size × Black				50.812		11.460
SW F-stat.: Ln wildfire size × Hispanic					14.147	7.049
Obs.	103080	103080	90069	103080	103080	90069
R^2	0.642	0.652	0.642	0.659	0.655	0.645

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

	(1)	(2)	(3)	(4)	(5)	(6)
Ln Wildfire Size	1.003	1.794	1.679	1.678	0.376	0.416
	(0.763)	(0.747)	(1.398)	(0.830)	(0.785)	(0.628)
Ln Wildfire Size × Age	1.465					0.632
	(0.504)					(0.616)
Ln Wildfire Size × Unmarried		-1.316				-0.734
		(0.596)				(1.177)
Ln Wildfire Size × High School or Less			1.279			-0.052
			(1.089)			(0.507)
Ln Wildfire Size × Black				-1.284		-0.544
				(0.304)		(0.691)
Ln Wildfire Size × Hispanic					1.883	0.601
					(1.026)	(0.930)
SW F-stat.: Ln wildfire size	34.160	31.574	12.690	37.616	54.959	14.719
SW F-stat.: Ln wildfire size × Age	53.734					94.971
SW F-stat.: Ln wildfire size × Unmarried		51.771				17.625
SW F-stat.: Ln wildfire size × High School or Less			5.714			68.990
SW F-stat.: Ln wildfire size × Black				50.812		11.460
SW F-stat.: Ln wildfire size × Hispanic					14.147	7.049
Obs.	103080	103080	90069	103080	103080	90069
R^2	0.326	0.319	0.305	0.323	0.316	0.321

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

	(1)	(2)	(3)	(4)	(5)	(6)
Ln Wildfire Size	-0.013	-0.017	-0.021	-0.016	-0.002	-0.005
	(0.011)	(0.011)	(0.021)	(0.013)	(0.009)	(0.010)
Ln Wildfire Size × Age	-0.007					0.002
	(0.006)					(0.008)
Ln Wildfire Size × Unmarried		0.009				0.005
		(0.006)				(0.015)
Ln Wildfire Size × High School or Less			-0.006			0.008
			(0.015)			(0.007)
Ln Wildfire Size × Black				0.016		0.012
				(0.005)		(0.009)
Ln Wildfire Size × Hispanic					-0.021	-0.017
					(0.015)	(0.016)
SW F-stat.: Ln wildfire size	34.160	31.574	12.690	37.616	54.959	14.719
SW F-stat.: Ln wildfire size × Age	53.734					94.971
SW F-stat.: Ln wildfire size × Unmarried		51.771				17.625
SW F-stat.: Ln wildfire size × High School or Less			5.714			68.990
SW F-stat.: Ln wildfire size × Black				50.812		11.460
SW F-stat.: Ln wildfire size × Hispanic					14.147	7.049
Obs.	103080	103080	90069	103080	103080	90069
R^2	0.499	0.491	0.481	0.483	0.478	0.460

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

	(1)	(2)	(3)	(4)	(5)	(6)
Ln Wildfire Size	2.682	3.120	3.363	3.098	0.867	1.152
	(1.613)	(1.656)	(2.877)	(1.784)	(1.287)	(1.284)
Ln Wildfire Size × Age	0.675					0.362
	(0.695)					(0.887)
Ln Wildfire Size × Unmarried		-0.254				0.164
		(0.757)				(1.733)
Ln Wildfire Size × High School or Less			0.931			-0.868
			(1.903)			(0.907)
Ln Wildfire Size × Black				-1.542		-1.185
				(0.648)		(1.059)
Ln Wildfire Size × Hispanic					3.296	1.921
					(2.131)	(2.043)
SW F-stat.: Ln wildfire size	34.160	31.574	12.690	37.616	54.959	14.719
SW F-stat.: Ln wildfire size × Age	53.734					94.971
SW F-stat.: Ln wildfire size × Unmarried		51.771				17.625
SW F-stat.: Ln wildfire size × High School or Less			5.714			68.990
SW F-stat.: Ln wildfire size × Black				50.812		11.460
SW F-stat.: Ln wildfire size × Hispanic					14.147	7.049
Obs.	103080	103080	90069	103080	103080	90069
R^2	0.351	0.347	0.329	0.338	0.318	0.328

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.

D.2 Without Large Fires

Table D.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	-7.026	2.126	-0.024	4.160
	(2.377)	(1.049)	(0.015)	(2.167)
County FE	X	X	X	X
Year-Month FE	X	X	X	X
Fire Weather Controls	X	X	X	X
Kleibergen-Paap F-stat.	39.358	39.358	39.358	39.358
Counties	576	576	576	576
Obs.	101619	101619	101619	101619
R^2	0.650	0.326	0.487	0.330

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.

E Evidence from Wind Direction

E.1 Empirical Strategy

The empirical strategy based on Rangel and Vogl (2019) and He et al. (2020) is to estimate the differential impact of upwind and downwind fire. The estimation equation is as follows:

$$Y_{it} = \beta_1 Upfire_{it} + \beta_2 Downfire_{it} + \gamma X_{it} + \lambda_i + \lambda_t + \epsilon_{it} \tag{E.1}$$

where Y_{it} is the outcome of interest for county i at time t. $Upfire_{it}$ and $Downfire_{it}$ are the sizes of wildfires in upwind and downwind fires, respectively. The interest of the estimate is the differential impact of upwind and downwind fire, β_1 - β_2. Eq.(E.1) also includes weather controls (X_{it}), time fixed effects (λ_i), and county fixed effects (λ_t). The estimation in this study defines upwind fires and downwind fires as wildfires at an upwind and downwind angle of 90 degrees, respectively, with a radius of 50 km from geographic centers. Alternative specifications using different angles (45 degrees) and radii (70 km and 90 km) do not significantly alter the magnitudes or standard deviations significantly[36]. The identifying assumption is that upwind fires and downwind fires are equally correlated with covariant and that upwind fires increase pollution more than downwind fires do.

E.2 Estimation Results

[36]These results are available upon request.

Table E.8: Wildfires and Pollution: Wind Direction, 2003-2018

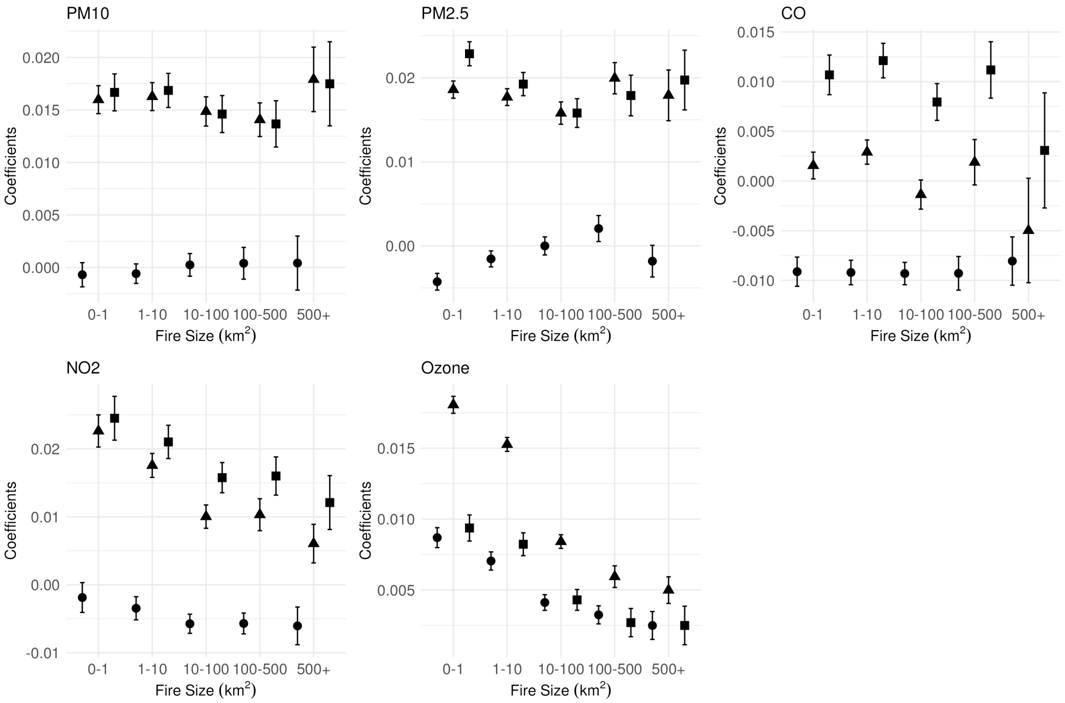
	Particulate Pollutants		Gaseous Pollutants							
	PM_{10}	$PM_{2.5}$	CO	NO_2	O_3	1,3-Butadiene	Benzen	Styrene	n-Hexane	NMVOC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Ln Upwind fire size (50km)	0.016	0.018	0.002	0.019	0.016	-0.002	0.008	0.003	0.013	0.012
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)
Ln Downwind fire size (50km)	0.000	-0.003	-0.009	-0.003	0.007	-0.009	-0.011	-0.007	-0.003	-0.007
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)	(0.004)
Wald Estimates (Upwind - Downwind)	0.016	0.021	0.011	0.023	0.009	0.007	0.019	0.010	0.016	0.019
	0.002	0.001	0.002	0.003	0.001	0.004	0.003	0.004	0.004	0.004
β_{wind} / $\beta_{lightning}$	0.167	0.039	0.039	0.025	0.014	0.013	0.024	0.032	0.011	0.011
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
Other Weather Controls	X	X	X	X	X	X	X	X	X	X
Mean (Dep. Var.)	21.012	9.589	0.370	9.197	32.038	0.340	1.621	0.479	1.505	123.898
SD (Dep. Var.)	24.206	6.759	0.259	7.492	11.678	1.317	10.806	4.090	12.076	185.641
Counties	594	831	298	373	909	859	965	905	616	406
Obs.	1187747	1824927	1062609	1334983	3555742	352876	746912	543776	565828	552252
R2	0.492	0.407	0.446	0.716	0.479	0.508	0.515	0.478	0.553	0.532

Notes: 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. The Wald estimates shows the differences of coefficients between upwind fires and downwind fires. Standard errors clustered by county are shown in parentheses.

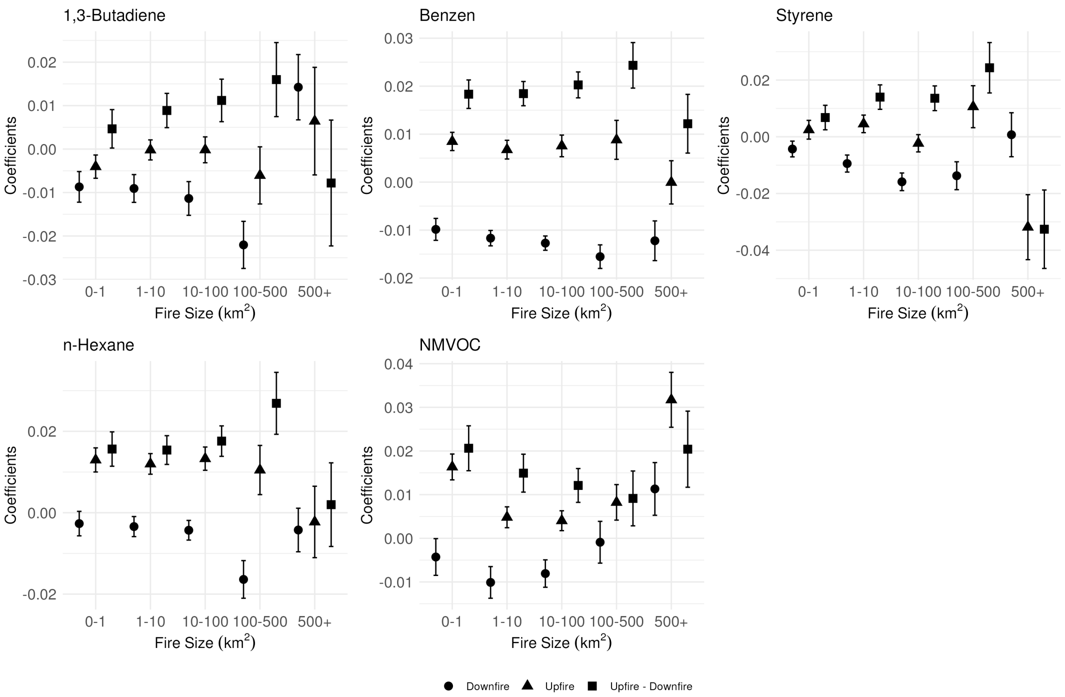
Table E.9: Wildfires and Health: Wind Direction, 2003-2018

	Birth Weight		Gestational Age	
	Grams	Low Birth Weight per 1,000	Weeks	Premature per 1,000
	(1)	(2)	(3)	(4)
Ln Upwind fire size (50km)	0.067	-0.056	0.000	-0.036
	(0.094)	(0.044)	(0.001)	(0.061)
Ln Downwind fire size (50km)	0.082	0.020	-0.001	-0.065
	(0.097)	(0.042)	(0.001)	(0.063)
Wald Estimates (Upwind - Downwind)	-0.014	-0.076	0.001	0.029
	0.127	0.061	0.001	0.080
County FE	X	X	X	X
Year-Month FE	X	X	X	X
Fire Weather Controls	X	X	X	X
Other Weather Controls	X	X	X	X
Mean (Dep. Var.)	3279.471	78.304	38.628	116.910
SD (Dep. Var.)	76.443	26.131	0.302	34.819
Counties	576	576	576	576
Obs.	103080	103080	103080	103080
R2	0.673	0.343	0.504	0.369

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 date fixed effects. The Wald estimates shows the differences of coefficients between upwind fires and downwind fires. Standard errors clustered by county are shown in parentheses.



(a) Criteria Pollutants



(b) Volatile Organic Compounds (VOCs)

Figure E.2: Flexible Specifications of Wildfires and Pollution (Wind Direction), 2003-2018

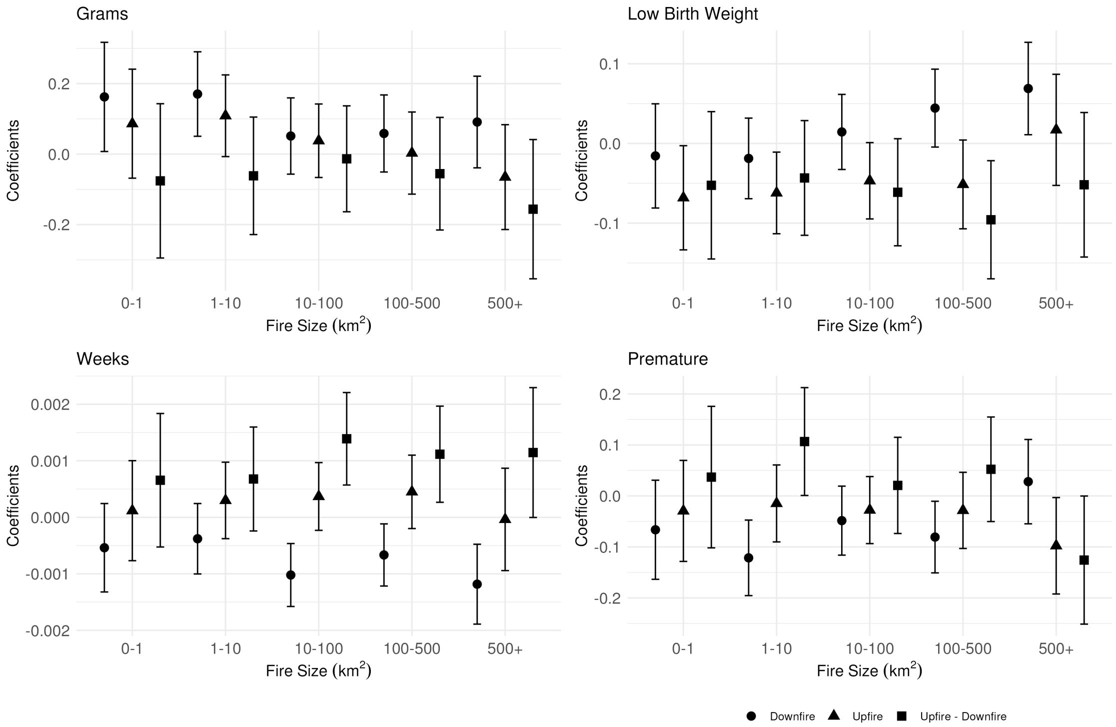


Figure E.3: Flexible Specifications of Wildfires and Pregnancy Outcomes (Wind Direction), 2003-2018

F Placebo Tests: No Wildfire Sample

Table F.10: Placebo Tests: No Wildfire Sample

	Birth Weight (1)	Low Birth Weight (2)	Gestational Age (3)	Premature (4)
Lightning Count / 1000	-0.059	0.036	0.000	0.087
	(0.090)	(0.044)	(0.000)	(0.052)
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.	33038	33038	33038	33038
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.

G TWFE Robust Estimator

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

	TWFE		BJS	
	Reduced	Wald	Reduced	Wald
	(1)	(2)	(3)	(4)
Birth Weight (Grams)				
1[Lightning ≥ 10000]	-1.558	-4.979	-1.962***	-5.175
	(0.662)		(0.685)	
Low Birth Weight per 1,000				
1[Lightning ≥ 10000]	0.427	1.363	0.559	1.475
	(0.332)		(0.347)	
Gestational Age (Weeks)				
1[Lightning ≥ 10000]	-0.007	-0.022	-0.008**	-0.021
	(0.004)		(0.004)	
Premature per 1,000				
1[Lightning ≥ 10000]	0.827	2.642	0.788	2.077
	(0.518)		(0.506)	
First-stage				
1[Lightning ≥ 10000]	0.313		0.379***	
	(0.051)		(0.050)	
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.

H Robustness Checks for Log with Zeros

Table H.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	-4.750	-4.533	-4.533	-4.538	-4.549	-4.559
	(1.904)	(2.016)	(2.019)	(2.056)	(2.144)	(2.240)
R^2	0.662	0.622	0.622	0.614	0.594	0.571
Panel B: Low Birth Weight per 1,000						
Ln Wildfire Size	1.495	1.427	1.427	1.429	1.432	1.435
	(0.788)	(0.803)	(0.804)	(0.813)	(0.836)	(0.862)
R^2	0.334	0.301	0.300	0.294	0.277	0.257
Panel C: Gestational Age (Weeks)						
Ln Wildfire Size	-0.015	-0.014	-0.014	-0.015	-0.015	-0.015
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
R^2	0.497	0.472	0.472	0.466	0.454	0.439
Panel D: Premature per 1,000						
Ln Wildfire Size	2.814	2.685	2.685	2.688	2.695	2.701
	(1.699)	(1.689)	(1.691)	(1.705)	(1.742)	(1.782)
R^2	0.350	0.284	0.282	0.269	0.235	0.196
Kleibergen-Paap F-stat.	35.752	15.863	14.195	15.686	11.458	9.355

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.

I Robustness Checks for Spatial Correlation

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

	Grams (1)	LBW (2)	Weeks (3)	Premature (4)
Ln Wildfire Size	-4.875	1.516	-0.015	2.920
	(2.050)	(0.826)	(0.012)	(1.810)
County FE	X	X	X	X
Year-Month FE	X	X	X	X
Fire Weather Controls	X	X	X	X
First-Stage F-stat.	8.211	8.211	8.211	8.211
Counties	576	576	576	576
Obs.	103080	103080	103080	103080
R^2	0.661	0.333	0.497	0.349

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.