Infant Health in the Age of Megafires: Evidence from U.S. Wildfire Smoke Exposure

Laura Alcocer Quiñones Jamie Hansen-Lewis *

February 18, 2026

We quantify the impact of wildfire smoke on infant health across the United States. Climate change and historical fire suppression have dramatically increased wildfire frequency and severity in recent decades. We assemble a national dataset from 2007 to 2017 of birth records, fires, and gestational smoke exposure. Our results imply that smoke has a much more muted effect on infant health overall than the findings of existing estimates that rely on more limited settings and fewer outcomes. Additional results illustrate how the salience of smoke near fires plays a significant role in mitigating adverse health effects. Overall, our findings underscore the potential value of information interventions and adaptation to reduce future damages from smoke.

*Alcocer is PhD Candidate in the Department of Agricultural and Resource Economics at the University of California, Davis (email: lalcocer@ucdavis.edu). Hansen-Lewis is Assistant Professor in the Department of Agricultural and Resource Economics at the University of California, Davis (email: jhansen-lewis@ucdavis.edu). We gratefully acknowledge financial support for this project from the Giannini Foundation of Agricultural Economics as well as the USDA National Institute of Food and Agriculture, Hatch project 7010035. For helpful comments, we thank Michelle Marcus, Dalia Ghanem, Marianne Bitler, Clara Berestycki, Rhiannon Jerch, Katrina Jessoe, and participants at Western Economic Association International. For excellent research assistance, we thank Dasha Ageikina. All remaining errors are our own.

1 Introduction

Climate change and historical fire suppression have dramatically increased wildfire frequency and severity in recent decades. As a result, wildfires are a significant and growing source of air pollution exposure in the United States (van Donkelaar et al., 2019). Despite this threat, evidence of the health damages of air pollution is largely derived from non-wildfire sources, such as industrial and transportation emissions (Graff Zivin and Neidell, 2013; Currie and Walker, 2019). Wildfire smoke could be more harmful to human health than air pollution from other sources because fire smoke can occur at very high levels and mixes many types of pollutants. Conversely, several factors could lessen the damages of smoke. Wildfire smoke is very salient, and occasionally avoidable. Further, wildfire smoke emissions typically originate further from populated areas than emissions of non-wildfire sources. Distinguishing the unique impacts of wildfire smoke is important for managing fire-prone land, regulating wildfire and prescribed fire smoke, and documenting the impacts of climate change.

Several challenges make it difficult to determine the effects of fire smoke on infant health. A first challenge is isolating the effect of smoke from the effect of wildfires. Extreme fires cause displacement and economic damage. Further, areas in the immediate vicinity of wildfires differ from locations with smoke far from fires because smoke is more salient nearby a fire, suggesting people will adjust their behavior to avoid exposure. A second challenge is that the effects of smoke may be nonlinear because smoke varies in intensity and duration. A final challenge to isolating the effect of smoke is accounting for the role of behavioral responses to avoid exposure and lessen the health damages.

In this paper, we are the first to comprehensively quantify how wildfire smoke impacts infant health outcomes in the United States. We assemble a county-year-month panel dataset from 2007 to 2017 for the contiguous United States that links birth outcomes, wildfire smoke, and wildfire occurrence. Our primary outcomes of interest are rate of low birth weight birth and rate of preterm births from comprehensive records of birth certificates in NCHS (2017). Given counties and dates of birth, we link these outcomes to pollution exposure over the gestation period. Our treatment is in-utero fine particulate matter ($PM_{2.5}$) from wildfire smoke from Childs et al. (2022). We tie smoke data to records of wildfires from Short (2023).

We estimate the impacts of smoke on infant health with a panel regression of the

outcomes on in-utero smoke and fire exposure. We measure both the effect of a one microgram per cubic meter (μgm^{-3}) increase in mean in-utero smoke $PM_{2.5}$ for births without a wildfire nearby and the additional effect of a one μgm^{-3} increase in mean in-utero smoke $PM_{2.5}$ for births with a wildfire nearby. In additional results, we allow for a nonlinear relationship between $PM_{2.5}$ and infant health outcomes and between distance to a fire and the marginal damages of $PM_{2.5}$. We also test for heterogeneous effects across demographic groups with varying avoidance capabilities.

To account for the role of behavioral responses in the main results, we supplement the dataset with records of Google search trends for queries related to fires, air quality, and defensive investments. Google search trends serve as a proxy for salience and adaptation in that searches should increase at the same time and in the same locations as exposure to wildfire smoke if the exposed population is aware of a fire. We then estimate the effect of smoke and proximity to a fire on search trends and test whether the effect of smoke on searches is greater in locations nearby a wildfire.

Overall, we find in-utero exposure to wildfire smoke significantly increased preterm births but had a negligible effect on low birth weight births. As a comparison to other pollution sources, we estimate that the marginal damages of one μgm^{-3} of smoke $PM_{2.5}$ on the rate of low weight births are under one fifth the magnitude of one μgm^{-3} of $PM_{2.5}$ from diesel emissions (Alexander and Schwandt, 2022). We further illustrate that the degree of damages differ significantly based on proximity to a wildfire. Among births distant from wildfire, we estimate that the mean in-utero smoke $PM_{2.5}$ of 0.33 μgm^{-3} results in a 0.40% (0.12, 0.67; 95% CI) increase in the rate of low birth weight and 0.71% (0.43, 0.98; 95% CI) increase in the rate of preterm births. By contrast, among births near a wildfire, at the mean in-utero smoke $PM_{2.5}$ of 0.36 μgm^{-3}, we find a less than 0.01% (-0.55, 0.57; 95% CI) increase in the rate of low birth weight and 0.40% (-0.19, 0.98; 95% CI) increase in the rate of preterm births. Our analysis of Google search trends and prenatal care visits corroborates our health findings and supports the interpretation that adaptation to smoke is higher among mothers nearby fires. For a one unit increase in smoke $PM_{2.5}$, prenatal care visits and searches for terms related to air purification rise more nearby fires than further away.

A growing literature examines the human health effects of wildfire smoke in the United States and other settings. With respect to health effects, a key focus has been

on the mortality burden of wildfire smoke at all ages (Qiu et al., 2025; Ma et al., 2024; Ye et al., 2022) and especially for the elderly (Miller et al., 2025) and infants (Pullabhotla et al., 2023; Jayachandran, 2009). Related work within and outside of economics has highlighted the relevance of smoke to adult morbidity, especially cardiopulmonary illness (Krall et al., 2017; Liu and Peng, 2019; Peng et al., 2009; Moeltner et al., 2013; Lee et al., 2024; Aguilera et al., 2021; DeFlorio-Barker et al., 2019; Heft-Neal et al., 2023; Wettstein et al., 2018; Delfino et al., 2009). In addition to health effects, several studies have highlighted the role of wildfire smoke in labor markets (Borgschulte et al., 2022; Lee and Beatty, 2024a,b). Gould et al. (2024) provide a useful summary of the existing literature. We make three central additions to this body of knowledge.

First, no prior study has comprehensively measured the relationship between prenatal smoke exposure and infant health outcomes as documented on birth certificates in the United States. An array of studies illustrate that the infant health effects of environmental shocks, especially air pollution, are of central policy interest because they substantially influence human capital development and adult economic outcomes (Isen et al., 2017; Currie, 2011). Nevertheless, the closest existing work on wildfire smoke and infant health focuses on international settings such as Brazil (Rangel and Vogl, 2019). Estimates for the United States limit the geographic-scope to specific states, such as California (Heft-Neal et al., 2022), Georgia (Jones and Berrens, 2021), or Colorado (Mccoy and Zhao, 2021), and often measure effects only for subsets of infant health metrics, such as only preterm births or only birth weight. The broad picture of how fires affect infant health in the United States remains incomplete. This study provides evidence that delineates the full extent of infant health effects of smoke with respect to both varied measures of infant health and a comprehensive geographic scope in the United States.

Second, this study establishes the importance of proximity to a fire in the overall health costs of wildfire smoke. Although some heterogeneity has been acknowledged (Jones and McDermott, 2022; Rauscher and Cao, 2024), existing studies on the health effects of wildfire smoke have treated the marginal damages of smoke as equal regardless of distance to a wildfire. We illustrate that proximity to a fire, within roughly 50-100 kilometers, is a key mediating factor in the effect of smoke on health outcomes. We show this is likely because exposure to smoke within the close proximity of a fire coincides with both the direct economic effects of wildfires as well as greater salience, and thus

likely greater adaptive behavior, to the presence of smoke. Our finding that the effects of exposure to smoke are more pernicious when they are of lower salience is important in emphasizing the potential benefits of policy interventions that encourage avoidance of smoke.

Third, our results on differential search trends by proximity to a wildfire contribute evidence on the role of adaptation to an environmental shock in the setting of infant health. Prior to this study, a limited but growing body of research established that populations experiencing smoke deviated from typical location patterns (Lee and Beatty, 2024b) and increased Google search activity for keywords related to salience and defensive investments (Burke et al., 2022). Related evidence shows that air pollution changes time spent outside and purchases of defensive investments (Ward and Beatty, 2016; Deschenes et al., 2017). By showing smoke increased searches more near fires relative to far, this study confirms and extends the existing evidence of the overall effect of smoke on Google searches in Burke et al. (2022) and the effect of water pollution on searches in Christensen et al. (2023). Further, this paper's results on prenatal care visits add new evidence that suggests that pollution salience translates into behavioral responses.

2 Data

2.1 Health outcomes

We obtain the universe of birth certificates for 2005-2017 from the Center for Disease Control and Prevention's restricted-access National Vital Statistics System (NCHS, 2017). The data include details of individual births such as the birth weight in grams, gestation length in weeks, and mother's demographic characteristics alongside the county of the mother's residence and the month of birth. Data in counties with few births are excluded for anonymity. We further restrict the sample to singleton births in hospitals among mothers between ages 18 and 45 with non-missing birth date, birth weight, and gestation.

We focus on birth weight in grams, rate of preterm birth, and rate of low infant birth weight as our measures of infant health. Births before 37 weeks are classified as preterm and births with weight less than 2,500 grams are classified as low birth weight. Mother-infant variables included as controls are indicators for mother's years of education $\{<12, =12, 13-15\}$, mother's race $\{$Black$\}$, Hispanic, mother's age $\{19-24, 25-34, >$

$35\}$, two previous live births, three or more previous live births, and cigarette use during pregnancy. We collapse the individual birth outcomes to cells of births in the same county and month for computational efficiency.

2.2 Smoke exposure

The ambient $PM_{2.5}$ from wildfire smoke comes from Childs et al. (2022).The authors use smoke plumes from National Oceanic and Atmospheric Administration (NOAA) Office of Satellite and Product Operations (2003) and ground-based measures of $PM_{2.5}$, paired with machine-learning models, to predict $PM_{2.5}$ from wildfire smoke in μgm^{-3} at the county-day level. The sample includes the contiguous United States from 2006 to 2020. The panel in our analysis begins with births in 2007 as 2006 is the earliest year available to assign in-utero smoke. The main advantage of this data set is that it allows us to account for the intensity of smoke. The input data product of smoke plumes from National Oceanic and Atmospheric Administration (NOAA) Office of Satellite and Product Operations (2003), used in Miller et al. (2025), provides only coarse characterizations of ground-level smoke intensity.

We assign in-utero smoke $PM_{2.5}$ exposure to each birth. We first collapse the county-day of smoke $PM_{2.5}$ to county-month average smoke $PM_{2.5}$. Days without smoke are included as having zero $PM_{2.5}$. We then calculate the in-utero smoke $PM_{2.5}$ as the mean of county-month smoke $PM_{2.5}$ over the concurrent and eight preceding months.

Appendix A1 illustrates key features of in-utero smoke exposure. First, we find that while the median birth experienced 0.23 μgm^{-3} of smoke $PM_{2.5}$, the distribution is highly skewed. The average birth experienced 0.34 μgm^{-3} of smoke $PM_{2.5}$. Second, we note a modestly rising trend in smoke $PM_{2.5}$ and notable seasonality. Births in October and November have the highest average exposure whereas births in May and June have the lowest average exposure. Last, with respect to the spatial distribution of smoke $PM_{2.5}$, the counties with the highest average in-utero smoke exposure are in Montana, California and Idaho, whereas the counties with the lowest average exposure are in Arizona, Texas and New Mexico.

2.3 Wildfire exposure

To determine the births likely affected by the presence of a wildfire, we obtained the Fire Program Analysis Fire Occurrence Database (FPA FOD) (Short, 2023). The data

include the point of origin, accurate up to one mile, discovery date, and final fire size in acres. The key advantage of this source is that it collects and standardizes historical records from the authoritative federal, state, and local fire organizations. Short (2014) demonstrate that although there are a handful of states lacking complete records of non-federal fires, the data accurately represent the variation at the state-year level from other sources. There are two key limitations of the data. First, although the origin coordinates and size allow for an approximation of the fire extent, the records do not include the exact perimeters of burned area. Second, the fire containment date is missing in 33% of fires overall and 25% of fires over 100 acres. In cases where the containment date is missing we impute the date assuming these fires lasted one day. As an alternative, we subset to fires with a specified containment date in robustness checks.

The data include an average of 69,880 wildfire incidents and 5,304,357 burned acres per year. We construct a measure of in-utero fire exposure for each birth that indicates whether there was a fire with origin within 50 kilometers of the county's population weighted centroid during month of birth or any of the prior eight months. Because there are many small fires, 97 percent of fires are smaller than 100 acres, roughly 85% percent of births occur in a county within 50 kilometers of a wildfire within the nine months before birth.

As we are interested in isolating the wildfires that are significant enough to merit a behavioral response, we limit the sample of fires to those over 100 acres. Using this baseline, roughly 40% percent of births occur in a county within 50 kilometers of a wildfire over 100 acres within the nine months before birth. We define births in counties with centroids within 50 km of the fire origin as near a wildfire because wildfire safety protocol indicates that residents up to that distance face evacuation orders during wildfires U.S. Fire Administration (2022); however, we allow the effects of smoke to vary flexibly by distance to the nearest fire in subsequent results. We also demonstrate robustness to stricter definitions of significant wildfires, notably using only fires over 200 and 500 acres.

2.4 Weather and other county characteristics

We use records of county-day minimum temperature, maximum temperature, and total precipitation from PRISM Daily Weather Data for the Contiguous United States (Schlenker, 2020). We collect county-year-month levels of employment and unemployment from the Bureau of Labor Statistics (U.S. Department of Labor, 2024). We also

collate the number of women of reproductive age, 15-44 years old, for each county-year from National Cancer Institute, DCCPS, Surveillance Research Program (2022).

2.5 Google trends

To determine the extent to which distance to a fire plays a role in awareness and adaptation to smoke, we use Google trends data (Google Trends, 2017). This approach has been used before to establish awareness of wildfire smoke in (Burke et al., 2022). Google trends provides search data at the level of metropolitan areas that closely align with designated market areas (DMAs). We rely on the mapping of counties to Google's DMAs from Schneider (2025) to construct a timeseries of keyword searches from 2006 to 2017 at the month-designated market area (DMA) level. Our keywords include the terms: fire, wildfire, smoke, air quality, air filter, air purifier, and N95 mask. Appendix A.2 provides further details on this data.

2.6 Descriptive statistics

Table 1 illustrates key features of the setting. First, counties with high smoke are often far from fires. Second, demographic differences are minimal across counties with high and low exposure to smoke and fires. Last, smoke and fire exposure are correlated with meteorological characteristics. We include several variations of the meteorological controls in robustness exercises.

3 Effect of wildfire smoke on infant health

3.1 Empirical framework

We estimate the impacts of smoke on infant health with the following panel regression at the county i and year-month t level:

$$y_{it} = \alpha + \beta_1 s_{it} + \beta_2 s_{it} \text{fire}_{it} + \tau_{iq} + \phi_t + \rho X_{it} + \epsilon_{it} \tag{1}$$

where outcomes y_{it} include the rate of low weight infant births, rate of preterm births, gestational length, and mean birth weight. The central covariates of interest are s_{it}, the mean smoke $PM_{2.5}$ from t to t-*8* inclusive, the interaction of s_{it} and fire_{it}, an indicator of whether there was a fire of 100 acres or more within 50 km of the population-weighted centroid of i from t to t-*8* inclusive. Fixed effects are included for the county-quarter,

τ_{iq}, and year-month, ϕ_t. The vector of control variables X_{it} includes mother demographic characteristics, weather, and socioeconomic characteristics along with region-year fixed effects.[1] Observations are weighted by the number of births in county i in year-month t. Robust standard errors are clustered by county. The coefficients of interest are β_1 and β_2. β_1 measures the effect of a one μgm^{-3} increase in mean in-utero smoke $PM_{2.5}$ for births without a wildfire nearby. Meanwhile, β_2 measures the additional effect of a one μgm^{-3} increase in mean in-utero smoke $PM_{2.5}$ for births with a wildfire nearby.

We perform several additional procedures to assure the validity of the research design and the stability of our estimates under varying modeling choices. A concern is that there is selection whereby mothers exposed to the environmental shocks of smoke and fires are different than other mothers in way that would yield different infant health outcomes even in the absence of the environmental shocks. To test for differences in the demographic composition of mothers, we estimate equation 1 with a demographic index as the outcome, which should not vary with the environmental shocks in the absence of selection. In a second set of procedures, we gauge the sensitivity of the coefficients with number of variations of the fixed effects and weather controls. In a final set of procedures, we consider nonlinear functional forms that allow for variation in the marginal effects of in-utero smoke.

3.2 Results

Table 2 reports the results of estimating equation 1 with our main infant health outcomes, birth weight, rate of low birth weight births, gestational length, and rate of preterm birth. The results indicate that in-utero exposure to wildfire smoke lowers health among births without a wildfire nearby. For this group, a one unit increase in mean in-utero smoke $PM_{2.5}$ lowers average weight at birth 1.79 grams (column 1), increased the rate of low weight births by 0.76 per 1,000 (column 2), decreased average gestational age by 0.02 weeks (column 3), and increased the rate of preterm births by 2.14 per 1,000 (column 4).

[1] Demographic controls include the fraction of mothers with characteristics education $\{< 12, = 12, 13-15\}$, race $\{$Black$\}$, Hispanic, age $\{19-24, 25-34, > 35\}$, two previous live births, three or more previous live births, and cigarette use during pregnancy as well as the fraction of births missing records for mother education, Hispanic ethnicity, and cigarette use. Weather controls include the number of days in year-months t to t-*8* with maximum temperature above 90 degrees Fahrenheit, an indicator of whether precipitation in year-months t to t-*8* was in the top quartile of the sample, and an indicator of whether precipitation in year-months t to t-*8* was in the bottom quartile of the sample. Socioeconomic controls include the average unemployment rate from t to t-*2*, average unemployment rate from t-*3* to t-*5*, and average unemployment rate from t-*6* to t-*8*.

At the mean in-utero smoke $PM_{2.5}$ of 0.33 μgm^{-3} among births without a wildfire nearby, these effects translate to a 0.02% decline in mean birth weight, 0.40% increase in the rate of low birth weight, 0.01% decline in the average gestational age, and 0.71% increase in the rate of preterm births.

The results in Table 2 also show that the impact of in-utero exposure to wildfire smoke on infant health is significantly weaker for all outcomes among births with a wildfire nearby compared to births without a wildfire nearby. At the mean in-utero smoke $PM_{2.5}$ of 0.36 μgm^{-3} among births with a wildfire nearby, these effects translate to a 0.01% increase in mean birth weight, less than 0.01% increase in the rate of low birth weight, less than 0.01% decline in the average gestational age, and 0.40% increase in the rate of preterm births.

The results of Table 2 imply that wildfire smoke has a much more muted effect on infant health than the estimates of previous studies. Although definitions of in-utero wildfire smoke exposure differ, an existing study of California from 2006-2011 found the median days of wildfire smoke yields a 3.4% rise in rate of preterm births (Heft-Neal et al., 2022). The upper bound of the 95% confidence interval in Table 2 column 4 implies a 0.99% rise in the rate of preterm births at the mean of in-utero smoke $PM_{2.5}$ and a 0.74% rise at the median among births without a wildfire nearby.

To evaluate the overall magnitude of the effect of wildfire smoke on infant health, we calculate the additional low weight and preterm births per year as a result of smoke while allowing for the diminished effects in the presence of a wildfire. We find smoke led to an additional 572 (-331, 1,476; 95% CI) low weight births and 2,169 (678, 3,660; 95% CI) preterm births on average per year in the continental US. The results are depicted in Figure A5. We further compare the impact of a one μgm^{-3} rise in $PM_{2.5}$ on the rate of low weight births from smoke to the impact from other sources in the literature. Although differences across samples affect the comparisons, the evidence suggests that the marginal damages from smoke are under a third of the damages from maritime pollution in Hansen-Lewis and Marcus (2025) and under a fifth of those of diesel emissions in Alexander and Schwandt (2022).

3.3 Robustness

To evaluate the sensitivity of the estimates, Appendix Table A2 repeats the estimation of Table 2 columns 2 and 4 under varying assumptions. We estimate the coefficients with

three variations of the fixed effects. Relative to the baseline, we reduce the fixed effects to only county and year-month fixed effects, we replace the region-year and county season fixed effects with county and state-month fixed effects per Deryugina et al. (2019), and we expand the fixed effects to state-year in lieu of region-year. For all variations we find consistent significant negative effects of smoke on outcomes for births far from a wildfire and more muted effects for births near a wildfire. Besides fixed effects, the results also remain consistent when we include a more flexible function of weather control variables over gestation. Additionally, we consider alternative definitions of smoke exposure. In lieu of using the estimated smoke $PM_{2.5}$, we define exposure to wildfire smoke as the count of days during the 9 months prior to birth during which there was any smoke over the county of the mother's residence. We find an additional day of any in-utero smoke increased the rate of low birth weight (preterm birth) by 0.02 (0.03) per 1,000 births for births without a wildfire nearby with more muted effects for births with a wildfire nearby. Further, we find that the results remain consistent when we define exposure to a fire as the mother residing within 50 kilometers of a fire that burned at least 200 acres. We also find the results are robust to a definition of 500 acres. Finally, we illustrate that the precision largely remains when the standard errors are clustered at the state level.

We further investigate the impact of smoke while allowing for a nonlinear function of the effect of smoke on infant health. Several existing studies indicate that smoke has greater marginal effects on outcomes at higher levels of smoke (Miller et al., 2025; Heft-Neal et al., 2023). To examine nonlinearities in our setting, we estimate a step function that estimates the additional effects of mean in-utero smoke $PM_{2.5}$ at varying intervals relative to smoke $PM_{2.5}$ under 0.1 μgm^{-3}. Specifically we fit the following specification:

$$y_{it} = \alpha + \sum_{j} \big(\beta_{1j} \mathbb{1}(s_{it} \in j\text{th interval}) + \beta_{2j} \mathbb{1}(s_{it} \in j\text{th interval})\text{fire}_{it}\big) + \tau_i + \phi_t + \rho X_{it} + \epsilon_{it} \tag{2}$$

where intervals j are $[0, 0.1)$, $[0.1, 0.25)$, $[0.25, 0.5)$, $[0.5, 0.75)$, $[0.75, 1.0)$, and $[1.0, +\infty)$. We use in-utero smoke $PM_{2.5}$ exposure above one μgm^{-3} as the last bin because over 90% of our observations for in-utero smoke $PM_{2.5}$ are below one μgm^{-3}.

Figure 1 panels (a) and (b) report the effect of smoke on the rate of low weight births for births without and with a wildfire nearby respectively. Figures 1 (c) and (d) similarly report the effect of smoke on the rate of preterm birth. Among births far from wild-

fires, higher levels in-utero smoke have greater effects of a one μgm^{-3} increase in smoke $PM_{2.5}$ on rate of low weight births and preterm births than lower levels of in-utero smoke. Among births in the vicinity of wildfires, the effect of a one μgm^{-3} increase in smoke $PM_{2.5}$ remains near zero at levels of in-utero smoke below roughly 0.5 μgm^{-3} for the rate of low weight births and one μgm^{-3} for the rate of preterm births. In Appendix Figure A6, we illustrate a similar pattern with outcomes mean birth weight and gestation. We also allow for more granularity in the effects of smoke for births with over one μgm^{-3} smoke $PM_{2.5}$ in Appendix Figures A7 and A8. The results remain consistent throughout.

Figure 2 further probes the definition of exposure to fire in the effect of smoke on infant health outcomes. We modify equation 1 to allow the effect of smoke $PM_{2.5}$ to vary by a function of the distance to the nearest fire in-utero, $f(\mathrm{d}_{it})$ in lieu of an indicator for the presence of a fire in-utero within 50km, fire_{it}. We use a quartic polynomial of distance to the nearest fire from t to $t-8$ inclusive of 100 acres or greater for $f(\mathrm{d}_{it})$. Figure 2 (a) reports the estimated marginal effect of a one μgm^{-3} increase in smoke $PM_{2.5}$ on the rate of low birth weight by distance to the nearest fire of 100 acres or greater. We repeat the analysis with the rate of preterm birth as the outcome and with a quartic polynomial of distance to a fire 500 acres or greater Figure 2 (b)-(d). In all scenarios, the marginal damages of smoke $PM_{2.5}$ are smaller at distances under roughly 100 km and remain nearly constant at greater distances. Further, the estimates are consistent with the baseline estimates of the effect of smoke using an indicator for the presence of a fire within 50 kilometers.

3.4 Additional outcomes

We report the results of estimating equation 1 with a set of supplemental outcomes in Table A3. First, we consider placebo outcomes to evaluate the validity of the research design. We failed to find any patterns in placebo outcomes that would indicate smoke $PM_{2.5}$ is correlated with other observable economic or demographic changes that would also effect infant health. Table A3 column 1 shows there is no significant effect of smoke $PM_{2.5}$ on an index of the demographic composition of mothers. Similarly, column 2 shows there is no effect of smoke on the unemployment rate.

We next consider the influence of "harvesting" on the main results. A concern in the infant health literature is that if an environmental shock leads to miscarriages, the subsequent surviving births may be perversely healthier on average than if weaker fetuses

had survived. To examine this channel, we estimate the effect of in-utero smoke $PM_{2.5}$ on the fertility rate and the rate of healthy births per woman of reproductive age. The advantage using the rate of healthy births per woman of reproductive age in lieu of rate of unhealthy births per birth is that the rate of healthy births per woman of reproductive age unambiguously declines if both the rate of healthy births per birth and the rate of births per woman fall (Ospino, 2023). We find evidence suggestive of harvesting as Table A3 column 3 shows a decline in the fertility rate in the presence of smoke. We also find a consistent pattern of adverse smoke effects when we consider the rate of healthy births per woman of reproductive age as the outcome. Although these alternative outcomes do not enable us to quantify the extent of harvesting in the main results, they indicate that there exist additional adverse fetal and infant health outcomes that are not captured in the baseline estimates for births both near and far from fires.

3.5 Heterogeneity

We explore heterogeneity over levels of mother education. Table A4 reports the results of estimating equation 1 at the individual level with the added flexibility of different effects of smoke both near and far from fires for mothers that had at least a high school education. Among births that are far from a fire, we find that the effects of smoke $PM_{2.5}$ on birth weight and low birth weight are significantly worse among infants of mothers without a high school education relative to those with a high school education. Among births that are near a fire, we find that the effects of smoke $PM_{2.5}$ on infant health outcomes are similar across mother education levels. Taken together, the results indicate that the most adverse effects of smoke occur when both salience and education are low. Although we measure the effect of smoke $PM_{2.5}$ rather than the overall effect of the presence of a fire, our results align broadly with past evidence showing that the effects of a fire on the rate of low birth weight are worse among mothers without a high school education relative to those with a high school education (Rauscher and Cao, 2024).

4 Adaptation in the presence of wildfire smoke

Given the importance of proximity to a wildfire in the impact of smoke on natality outcomes, this section examines how populations with proximity to a wildfire differ in ways that indicate they adapt to mitigate the damages of smoke. Although research has demonstrated a number of adaptations to fires and severe smoke, such as relocation, direct

observation of increased mitigating behaviors, such as wearing a mask or using an air filter, is difficult to establish because the purchase of such products often occurs before or after fires. Greater salience of smoke is a first-order indication that greater adaptive behaviors like wearing masks and operating air filters are being taken. In this section, we test for an increase in Google searches for terms related to wildfire smoke and defensive investments in areas in the vicinity of wildfires relative to areas further away. We also consider the number of prenatal care visits as a proxy for mothers' mitigative behavior.

4.1 Empirical framework

We repeat the regression of Equation 1 with a panel of designated market areas (DMA)-months. For designated market area (DMA) d in month-year t, let y_{dt} be a normalized index of Google search activity for keywords y including "fire", "wildfire", "smoke", "air quality", "air filter", "air purifier", and "N95 mask". As multiple counties are included in a single DMA, we restructure the independent variables to the DMA-year-month unit of observation. We define proximity to a fire, fire_{dt}, as the birth-weighted fraction of counties within DMA d with a fire of 100 acres or more within 50 km of the county's population-weighted centroid in the current month t. Similarly, we define DMA-year-month smoke, s_{dt}, as birth-weighted average of in-utero county-year-month smoke from t to t-8, s_{it}, for counties within DMA d. Like smoke, we define controls X_{dt} birth-weighted average of county-year-month controls X_{it}. Fixed effects include DMA-quarter, month-year, and region-year. The key difference with Google keyword outcomes relative to infant health outcomes is that we measure the effect of contemporaneous fire on searches at time t rather than the relationship between fire and searches over gestation. We also repeat the estimation of equation 1 with an indicator for whether the mother obtained the median prenatal care visits, 11, or greater as the outcome.

4.2 Results

Table 3 shows the results for the effect of smoke on Google search frequency for our keywords of interest. For all keywords, greater prevalence of nearby fires significantly increases the effect of smoke $PM_{2.5}$ on search frequency. With respect to how fires alter the salience of smoke, we find that for each 10 percent of the DMA population in the vicinity of a fire, the effect of an additional one μgm^{-3} of smoke $PM_{2.5}$ on search frequency increases 1.01 percentage points of the DMA maximum for "fire" (column 1), 0.82 per-

centage points for "wildfire" (column 2), 0.57 percentage points for "smoke" (column 3), and 0.68 percentage points for "air quality" (column 4). Alongside additional interest in salience-related terms in proximity to a fire, we also find added interest in terms for defensive investments. Searches for "air filter", "air purifier", and "N95 mask" also rise significantly more with fire presence which indicates additional behavioral changes that mitigate the health damages of smoke (columns 5-7). Although we find evidence that smoke $PM_{2.5}$ raises the salience of wildfires and air quality even when no one in the DMA is in the vicinity of a fire, we only find significant effects of smoke $PM_{2.5}$ on searches for defensive investments when fires are present. Overall, these results highlight a higher degree of smoke salience and adaptive behavior among individuals near a fire relative to those experiencing smoke further away.

Table 2 column 5 presents further evidence of additional adaptive behavior among mothers in proximity to a wildfire. We find that smoke $PM_{2.5}$ nearby a wildfire led to a significantly greater fraction of mothers with more than the typical number of prenatal care visits relative to mothers also experiencing smoke $PM_{2.5}$ further from a fire. This pattern suggests that higher salience of smoke close to wildfires relative to further away leads to behavioral adaptations that lessen the marginal damages.

5 Conclusion

In this paper, we estimate the impacts of wildfire smoke on infant health in the United States. We find differential effects based on proximity to a fire. We find that an additional μgm^{-3} of average in-utero smoke $PM_{2.5}$ for infants whose mothers were not nearby a wildfire decreases mean birth weight and gestational age while increasing the rate of low birth weight and preterm births. We also find that these impacts are weaker for infants whose mothers were nearby a wildfire. These distinct patterns highlight important differences that could be attributed to avoidance and adaptation.

Our setting extends on prior work on air pollution and infant health since $PM_{2.5}$ from wildfire smoke differs from regular $PM_{2.5}$. We illustrate how proximity, the degree of salience, and heightened exposure levels lead to heterogeneity in the marginal effects of smoke $PM_{2.5}$. With respect to proximity and salience specifically, we find that one unit of smoke $PM_{2.5}$ leads to additional prenatal care visits and Google searches for keywords indicative of salience and defensive investments near fires relative to further away.

Overall, our findings point to three main takeaways for policymakers. First, exposure to wildfire smoke, even at a distance from wildfire, damages infant health. Infants exposed in-utero are likely to suffer these consequences which can translate to adverse economic outcomes later in life. Second, policies to address the longstanding history of fire suppression, alongside climate change, may offer additional human capital benefits for the management of severe wildfires which have the most smoke dispersion. Third, public education interventions and the provision of information relating to wildfire events can aid in reducing the magnitude of these impacts. Providing the population with broader education on protective actions or the purchase of defensive investments can reduce health costs associated with wildfire smoke.

References

Aguilera, R., T. Corringham, A. Gershunov, and T. Benmarhnia (2021). Wildfire Smoke Impacts Respiratory Health More Than Fine Particles from Other Sources: Observational Evidence from Southern California. *Nature Communications 12*(1), 1493.

Alexander, D. and H. Schwandt (2022). The Impact of Car Pollution on Infant and Child Health: Evidence from Emissions Cheating. *The Review of Economic Studies 89*(6), 2872–2910.

Borgschulte, M., D. Molitor, and E. Y. Zou (2022). Air Pollution and the Labor Market: Evidence from Wildfire Smoke. *Review of Economics and Statistics*, 1–46.

Burke, M., S. Heft-Neal, J. Li, A. Driscoll, P. Baylis, M. Stigler, J. A. Weill, J. A. Burney, J. Wen, M. L. Childs, et al. (2022). Exposures and Behavioural Responses to Wildfire Smoke. *Nature Human Behaviour 6*(10), 1351–1361.

Childs, M. L., J. Li, J. Wen, S. Heft-Neal, A. Driscoll, S. Wang, C. F. Gould, M. Qiu, J. Burney, and M. Burke (2022). Daily Local-Level Estimates of Ambient Wildfire Smoke PM2.5 for the Contiguous US. *Environmental Science & Technology 56*(19), 13607–13621 (accessed 03/14/2024).

Christensen, P., D. A. Keiser, and G. E. Lade (2023). Economic Effects of Environmental Crises: Evidence from Flint, Michigan. *American Economic Journal: Economic Policy 15*(1), 196–232.

Currie, J. (2011). Inequality at Birth: Some Causes and Consequences. *American Economic Review 101*(3), 1–22.

Currie, J. and R. Walker (2011). Traffic Congestion and Infant Health: Evidence from E-ZPass. *American Economic Journal: Applied Economics 3*(1), 65–90.

Currie, J. and R. Walker (2019). What Do Economists Have to Say about the Clean Air Act 50 Years after the Establishment of the Environmental Protection Agency? *Journal of Economic Perspectives 33*(4), 3–26.

DeFlorio-Barker, S., J. Crooks, J. Reyes, and A. G. Rappold (2019, March). Cardiopulmonary Effects of Fine Particulate Matter Exposure among Older Adults, during Wildfire and Non-Wildfire Periods, in the United States 2008–2010. *Environmental Health Perspectives 127*(3), 037006.

Delfino, R. J., S. Brummel, J. Wu, H. Stern, B. Ostro, M. Lipsett, A. Winer, D. H. Street, L. Zhang, T. Tjoa, et al. (2009). The Relationship of Respiratory and Cardiovascular Hospital Admissions to the Southern California Wildfires of 2003. *Occupational and Environmental Medicine 66*(3), 189–197.

Deryugina, T., G. Heutel, N. H. Miller, D. Molitor, and J. Reif (2019). The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction. *American Economic Review 109*(12), 4178–4219.

Deschenes, O., M. Greenstone, and J. S. Shapiro (2017). Defensive Investments and the Demand for Air Quality: Evidence from the NOx Budget Program. *American Economic Review 107*(10), 2958–2989.

Google Trends (2006-2017). Accessed: 2025-04-11.

Gould, C. F., S. Heft-Neal, M. Johnson, J. Aguilera, M. Burke, and K. Nadeau (2024). Health Effects of Wildfire Smoke Exposure. *Annual Review of Medicine 75*(1), 277–292.

Graff Zivin, J. and M. Neidell (2013). Environment, Health, and Human Capital. *Journal of Economic Literature 51*(3), 689–730.

Hansen-Lewis, J. and M. Marcus (2025). Uncharted Waters: Effects of Maritime Emission Regulation. *American Economic Journal: Economic Policy 17*(1), 37–69.

Heft-Neal, S., A. Driscoll, W. Yang, G. Shaw, and M. Burke (2022). Associations between Wildfire Smoke Exposure during Pregnancy and Risk of Preterm Birth in California. *Environmental Research 203*, 111872.

Heft-Neal, S., C. F. Gould, M. L. Childs, M. V. Kiang, K. C. Nadeau, M. Duggan, E. Bendavid, and M. Burke (2023). Emergency Department Visits Respond Nonlinearly to Wildfire Smoke. *Proceedings of the National Academy of Sciences 120*(39), e2302409120.

Isen, A., M. Rossin-Slater, and W. R. Walker (2017). Every Breath You Take—Every Dollar You'll Make: The Long-Term Consequences of the Clean Air Act of 1970. *Journal of Political Economy 125*(3), 848–902.

Jayachandran, S. (2009). Air Quality and Early-Life Mortality: Evidence from Indonesia's Wildfires. *Journal of Human Resources 44*(4), 916–954.

Jones, B. A. and R. P. Berrens (2021). Prescribed Burns, Smoke Exposure, and Infant Health. *Contemporary Economic Policy 39*(2), 292–309.

Jones, B. A. and S. McDermott (2022). Infant Health Outcomes in Mega-Fire Affected Communities. *Applied Economics Letters 29*(14), 1325–1335.

Krall, J. R., J. A. Mulholland, A. G. Russell, S. Balachandran, A. Winquist, P. E. Tolbert, L. A. Waller, and S. E. Sarnat (2017). Associations Between Source-specific Fine Particulate Matter and Emergency Department Visits for Respiratory Disease in Four US Cities. *Environmental Health Perspectives 125*(1), 97–103.

Lee, G. and T. Beatty (2024a). Agricultural Burning and Agricultural-Worker Health. R&R at American Journal of Agricultural Economics.

Lee, G. and T. Beatty (2024b). Wildfires and Agricultural Worker Movement. *Journal of the Association of Environmental and Resource Economists (forthcoming)*.

Lee, J., A. J. Wilson, and S. Hsiang (2024). Simultaneous Measurement of Health Damage from Transboundary and Domestic Air Pollution in Mixture. Working paper.

Liu, J. C. and R. D. Peng (2019, November). The Impact of Wildfire Smoke on Compositions of Fine Particulate Matter by Ecoregion in the Western US. *Journal of Exposure Science & Environmental Epidemiology 29*(6), 765–776.

Ma, Y., E. Zang, Y. Liu, J. Wei, Y. Lu, H. M. Krumholz, M. L. Bell, and K. Chen (2024). Long-Term Exposure to Wildland Fire Smoke PM2.5 and Mortality in the Contiguous United States. *Proceedings of the National Academy of Sciences 121*(40), e2403960121.

Mccoy, S. J. and X. Zhao (2021). Wildfire and Infant Health: A Geospatial Approach to Estimating the Health Impacts of Wildfire Smoke Exposure. *Applied Economics Letters 28*(1), 32–37.

Miller, N. H., D. Molitor, and E. Zou (2025). The Nonlinear Effects of Air Pollution on Health: Evidence from Wildfire Smoke. Conditionally accepted, American Economic Review: Insights.

Moeltner, K., M.-K. Kim, E. Zhu, and W. Yang (2013). Wildfire Smoke and Health Impacts: A Closer Look at Fire Attributes and Their Marginal Effects. *Journal of Environmental Economics and Management 66*(3), 476–496.

National Cancer Institute, DCCPS, Surveillance Research Program (2022). Surveillance Epidemiology and End Results (SEER) Program Populations (1969-2020). `www.seer.cancer.gov/popdata`.

National Oceanic and Atmospheric Administration (NOAA) Office of Satellite and Product Operations (2003). Hazard Mapping System Fire and Smoke Product. `https://www.ospo.noaa.gov/Products/land/hms.html` (accessed 02/13/2024).

NCHS (2017). National Center for Health Statistics, Center for Disease Control and Prevention, Restricted-Use Natality Files: 2005 to 2017. `https://www.cdc.gov/nchs/nvss/nvss-restricted-data.htm` (accessed 10/27/2020).

New Jersey Department of Environmental Protection (2003). 2003 Air Quality Report. `https://nj.gov/dep/airmon/pdf/2003-nj-aq-report.pdf`.

Ospino, A. (2023). Does Free Health Care Mitigate the Effect of Prenatal Air Pollution on Birth Outcomes? `https://drive.google.com/file/d/1Rr-FN1aWyxlBop32K3mNISavIfxKQZMK/view` (accessed 6/3/2025).

Peng, R. D., M. L. Bell, A. S. Geyh, A. McDermott, S. L. Zeger, J. M. Samet, and F. Dominici (2009). Emergency Admissions for Cardiovascular and Respiratory Diseases and the Chemical Composition of Fine Particle Air Pollution. *Environmental Health Perspectives 117*(6), 957–963.

Pullabhotla, H. K., M. Zahid, S. Heft-Neal, V. Rathi, and M. Burke (2023). Global Biomass Fires and Infant Mortality. *Proceedings of the National Academy of Sciences 120*(23), e2218210120.

Qiu, M., J. Li, C. F. Gould, R. Jing, M. Kelp, M. L. Childs, J. Wen, Y. Xie, M. Lin, M. V. Kiang, et al. (2025). Wildfire Smoke Exposure and Mortality Burden in the US Under Climate Change. *Nature*, 1–3.

Rangel, M. A. and T. S. Vogl (2019). Agricultural Fires and Health at Birth. *Review of Economics and Statistics 101*(4), 616–630.

Rauscher, E. and X. Cao (2024). Unequal Effects of Wildfire Exposure on Infant Health by Maternal Education, 1995–2020. *RSF: The Russell Sage Foundation Journal of the Social Sciences 10*(1), 255–274.

Schlenker, W. (2020). "Daily Weather Data for Contiguous United States (1950-2019) - version march 2020". http://www.columbia.edu/~ws2162/links.html (accessed 03/05/2024).

Schneider, J. (2025). Google Trends Metro Area GIS Shape File. https://drive.google.com/open?id=1Gzu6MfQItuM60fm6TMF9IX6KAEJN7SO8 Accessed: 2025-09-17.

Short, K. C. (2014). A Spatial Database of Wildfires in the United States, 1992-2011. *Earth System Science Data 6*(1), 1–27.

Short, K. C. (2023). Spatial Wildfire Occurrence Data for the United States, 1992-2020 [FPA_FOD_20221014] (6th Edition). https://www.fs.usda.gov/rds/archive/catalog/RDS-2013-0009.6 (accessed 09/13/2024).

U.S. Department of Labor (2024). "Bureau of Labor Statistics. County Local Area Unemployment Statistics". https://download.bls.gov/pub/time.series/la (accessed 03/14/2024).

U.S. Fire Administration (2022). Wildfire Evacuation. https://www.usfa.fema.gov/wui/outreach/wildfire-evacuation.html (accessed 12/17/2024).

van Donkelaar, A., R. V. Martin, C. Li, and R. T. Burnett (2019). Regional Estimates of Chemical Composition of Fine Particulate Matter Using a Combined Geoscience-Statistical Method with Information from Satellites, Models, and Monitors. *Environmental Science & Technology 53*(5), 2595–2611.

Ward, A. L. S. and T. K. Beatty (2016). Who Responds to Air Quality Alerts? *Environmental and Resource Economics 65*, 487–511.

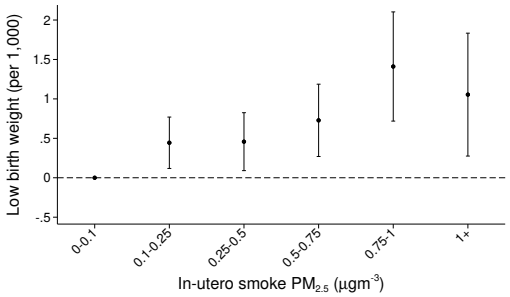
Wettstein, Z. S., S. Hoshiko, J. Fahimi, R. J. Harrison, W. E. Cascio, and A. G. Rappold (2018). Cardiovascular and Cerebrovascular Emergency Department Visits Associated With Wildfire Smoke Exposure in California in 2015. *Journal of the American Heart Association 7*(8), e007492.

Ye, T., R. Xu, X. Yue, G. Chen, P. Yu, M. S. Coêlho, P. H. Saldiva, M. J. Abramson, Y. Guo, and S. Li (2022). Short-term Exposure to Wildfire-Related PM2.5 Increases Mortality Risks and Burdens in Brazil. *Nature Communications 13*(1), 7651.

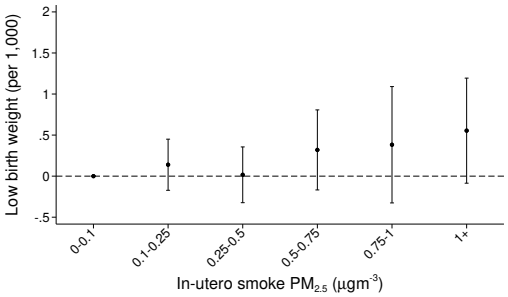
6 Figures

Figure 1: **Nonlinear Effects of Smoke $PM_{2.5}$ on Low Birth Weight and Preterm Birth**

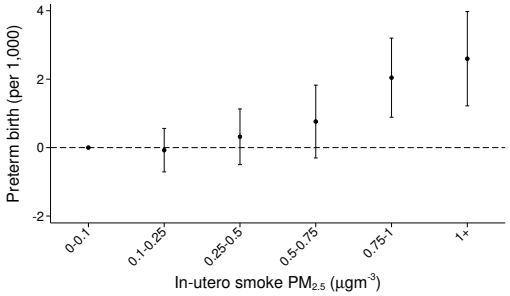
(a) *Low birth weight - no fire*



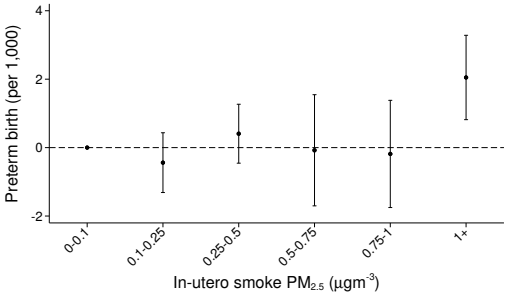
(b) *Low birth weight - near fire*



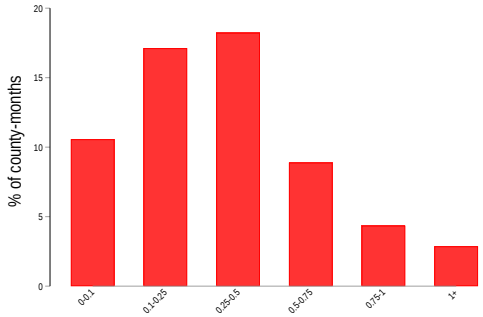
(c) *Preterm - no fire*



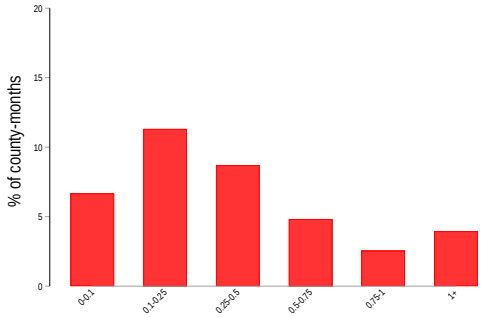
(d) *Preterm - near fire*



(e) *In-utero smoke PM2.5 - no fire*



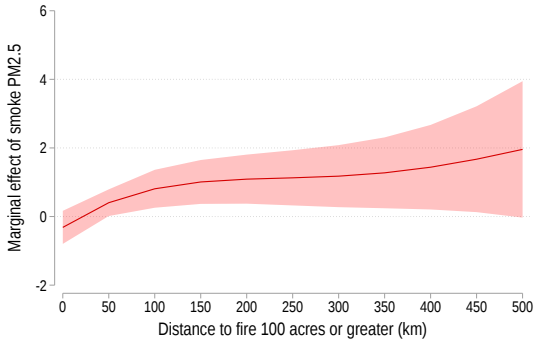
(f) *In-utero smoke PM2.5 - near fire*



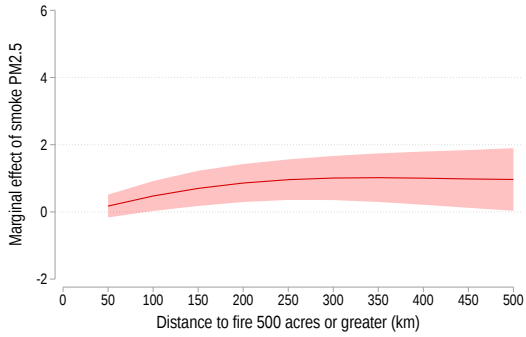
Notes: Estimated coefficients for nonlinear effects of smoke broken down by proximity to a fire. An observation is considered near fire if there was a fire of 100 acres or more within 50 km of the population-weighted county centroid from t to $t-8$ inclusive. Estimates obtained from equation 2. Panels (a) and (b) depict effects on the rate of low weight births per 1,000, panels (c) and (d) depict effects on the rate of preterm births per 1,000, and panels (e) and (f) provide the birth-weighted percentage of county-months that fall within the specified bin.

Figure 2: **Marginal Effects of Smoke $PM_{2.5}$ on Low Birth Weight and Preterm Birth by Distance from Fire**

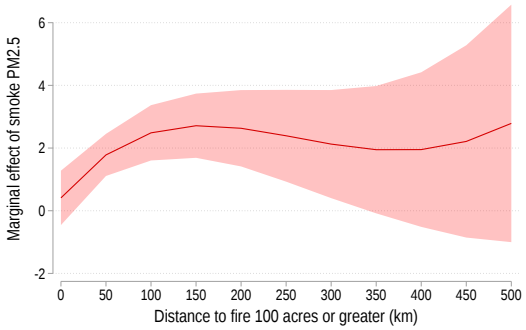
(a) *Low birth weight - fires ≥ 100 acres*



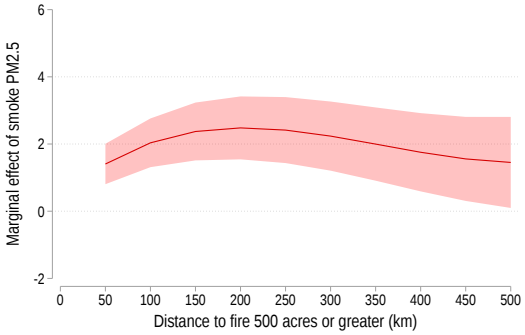
(b) *Low birth weight - fires ≥ 500 acres*



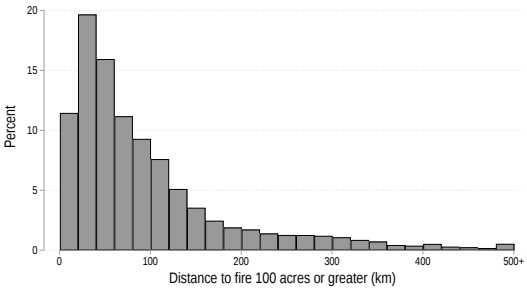
(c) *Preterm - fires ≥ 100 acres*



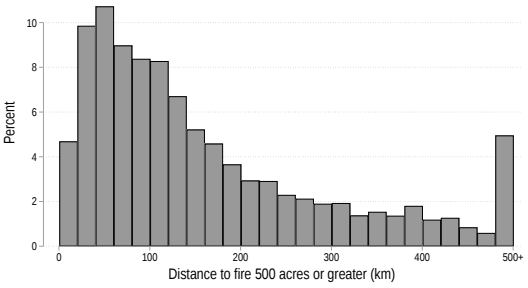
(d) *Preterm- fires ≥ 500 acres*



(e) *Histogram distance to fire ≥ 100 acres*



(f) *Histogram distance to fire ≥ 500 acres*



Notes: Graphs depict the estimated effect of a one μgm^{-3} increase in smoke $PM_{2.5}$ on rate of low weight births per 1,000 (panels (a) -(b)) and rate of preterm births per 1,000 (panels (c) -(d)) by distance to a fire 100 acres or greater (panels (a) and (c)) and distance to a fire 500 acres or greater (panels (c) and (d)). Lines depict the estimate of a quartic polynomial in distance and bands depict the 95% confidence interval with standard errors clustered at the county level. Histograms depict the percent of births at the given distance between the birth county centroid and the nearest ignition point of an in-utero fire at least 100 acres (panel (e)) and at least 500 acres (panel (f).

7 Tables

Table 1: **Summary Statistics 2007-2017**

		By level of smoke exposure		By type of exposure to fire	
	All counties	High	Low	Near fire	No fire
Panel A: Treatments					
In-utero smoke PM_2.5 (μgm^{-3})	0.34	0.57	0.11	0.36	0.33
Days with any smoke PM_2.5	3.64	4.45	2.83	4.19	3.28
In-utero fire (fraction)	0.40	0.37	0.42	1.00	0.00
Panel B: Infant health outcomes					
Low birth weight (per 1000)	63.37	63.22	63.52	63.16	63.50
Preterm (per 1000)	100.36	100.29	100.43	100.87	100.03
Birth weight (grams)	3,300.89	3,303.92	3,297.86	3,292.11	3,306.68
Gestational age (weeks)	38.73	38.73	38.73	38.70	38.75
Fertility rate per wma (per 1,000)	5.12	5.17	5.07	5.23	5.04
Not LBW per wma (per 1,000)	4.79	4.84	4.75	4.90	4.72
Not preterm per wma (per 1,000)	4.60	4.65	4.56	4.70	4.54
Panel C: County characteristics					
Number of women age 15-44 (wma)	255,843	226,152	285,524	351,873	192,574
Married	0.01	0.01	0.01	0.02	0.00
$<$ High School Ed.	0.14	0.14	0.14	0.16	0.13
Hispanic	0.01	0.01	0.01	0.01	0.01
Black	0.16	0.16	0.16	0.14	0.17
Over 35	0.15	0.15	0.16	0.15	0.15
Unemployment rate (per 1,000)	6.86	6.73	7.00	7.14	6.69
Days with temperature $>$ 90 °F	31.65	31.54	31.75	44.30	23.31
High precipitation	0.25	0.22	0.28	0.22	0.27
Low precipitation	0.26	0.21	0.31	0.43	0.15
Observations					
Observations county-month	403,064	228,698	174,366	152,975	250,089
Observations counties	3,109	3,107	3,109	2,674	3,080

Notes: The unit of observation is a county-year-month. Smoke $PM_{2.5}$ data is from Childs et al. (2022), population variables are from SEER, and natality outcomes and characteristics are from NCHS (2017). Not LBW per woman of maternal age and not preterm per woman of maternal age are weighted by women of maternal age. All other variables are weighted by the number of births. We restrict our sample to non-zero singleton births in a hospital from 2007 to 2017. An observation is classified as high smoke exposure if in-utero smoke $PM_{2.5}$ is above the sample median. An observation is classified as near fire if there was a fire of 100 acres or more within 50 km of the county population-weighted centroid from t to $t-8$ inclusive.

Table 2: **Effects of In-Utero Smoke on Infant Health and Prenatal Care**

	(1) Birth weight	(2) Low birth weight	(3) Gestation	(4) Preterm	(5) Prenatal care
In-utero smoke $PM_{2.5}$	-1.793	0.760	-0.016	2.143	2.511
	(0.798)**	(0.266)***	(0.004)***	(0.433)***	(4.345)
In-utero smoke $PM_{2.5}$ * fire	2.820	-0.738	0.015	-1.031	8.401
	(0.693)***	(0.234)***	(0.004)***	(0.398)***	(3.457)**
R^2	0.57	0.26	0.42	0.31	0.66
N	403,064	403,064	403,064	403,064	403,064
N-counties	3109	3109	3109	3109	3109
Mean	3300.89	63.37	38.73	100.36	575.69
%Change β_1	-0.018	0.395	-0.013	0.706	0.144
%Change $\beta_1 + \beta_2$	0.011	0.013	-0.001	0.397	0.685
Controls					
Region-by-year FE	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes
County-by-quarter FE	Yes	Yes	Yes	Yes	Yes
X_{imy}	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is the county-year-month. The sample includes counties in the continental United States from 2007-2017. The observations are weighted by the number of births in county i in year-month t. Estimates are obtained from equation 1. The independent variables are mean smoke $PM_{2.5}$ from t to t-8 and its interaction with an indicator of whether there was a fire of 100 acres or more within 50 km of the population-weighted centroid of i from t to t-8. The dependent variables are average birth weight in grams (column 1), rate of births per 1,000 less than 2,500 grams (column 2), average gestational age in weeks (column 3), rate of births per 1,000 less than 37 weeks gestation (column 4), and rate of births per 1,000 with 11 or more prenatal care visits (column 5). Robust standard errors clustered at the county level are reported in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: **Effects of In-Utero Smoke on Google Keyword Searches**

	(1) Fire	(2) Wildfire	(3) Smoke	(4) Air quality	(5) Air filter	(6) Air purifier	(7) N95 mask
In-utero smoke $PM_{2.5}$	0.582	1.078	0.177	1.250	0.121	-0.210	-0.032
	(0.371)	(0.347)***	(0.419)	(0.355)***	(0.557)	(0.430)	(0.714)
In-utero smoke $PM_{2.5}$ * fire	10.106	8.153	5.700	6.816	2.385	3.090	3.341
	(1.025)***	(1.227)***	(0.716)***	(1.008)***	(0.689)***	(1.092)***	(1.337)**
R^2	0.77	0.45	0.75	0.52	0.68	0.57	0.18
N	26,928	26,268	26,928	25,872	26,796	25,608	15,840
N-DMA	204	199	204	196	203	194	120
Mean	29.90	14.18	49.30	18.61	36.67	26.32	4.66
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DMA-by-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is the DMA-year-month. Each regression uses a balanced panel of designated market areas (DMAs) in the continental United States from 2007-2017. The independent variables are mean smoke $PM_{2.5}$ for DMA d from month t to t-8 and its interaction with the population-weighted fraction of counties in the DMA with a fire of 100 acres or more within 50 km of the county-centroid in month t. The dependent variables are Google trend search hits for DMA d in t, normalized between 0 and 100, for terms "Fire" (column 1), "Wildfire" (column 2), "Smoke" (column 3), "Air quality" (column 4), "Air filter" (column 5), "Air purifier" (column 6) and "N95 mask" (column 7). Robust standard errors clustered at the DMA are reported in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Online Appendix

Infant Health in the Age of Megafires: Evidence from U.S. Wildfire Smoke Exposure

Laura Alcocer Quiñones and Jamie Hansen-Lewis

Contents

A Data and Descriptive Statistics A2
A.1 Descriptive Statistics A2
A.2 Google Trends Data Description A3
B Additional Results and Robustness A5
B.1 Overall Magnitude A5
B.2 Robustness A7
B.3 Nonlinear Effects A8
B.4 Additional Outcomes A11

A Data and Descriptive Statistics

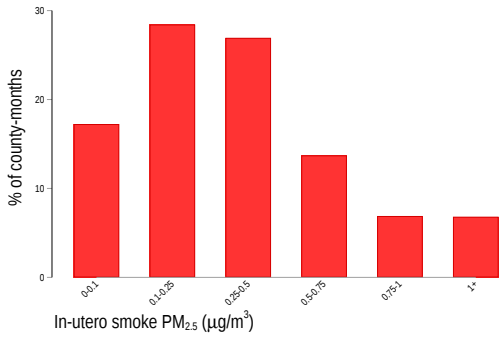
A.1 Descriptive Statistics

Figure A1 provides an overview of in-utero smoke $PM_{2.5}$. Smoke $PM_{2.5}$ is most frequent in the areas adjacent to mountain regions in the Pacific Northwest and California, the Upper Midwest, and the Southeast. It varies year to year, with 2007-2008 and 2011-2012 being the highest smoke $PM_{2.5}$ years in the sample, as well as seasonally with births in November being the most exposed and births in May the least exposed.

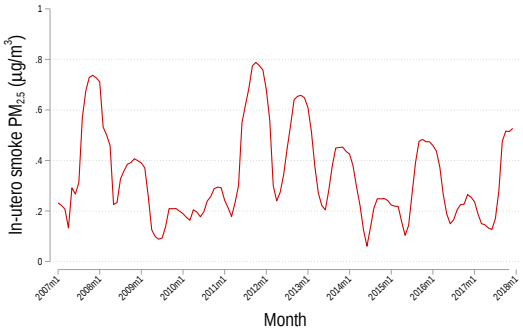
Figure A2 describes in-utero fire exposure. Roughly 97% of fires are under 100 acres. Among fires 100 acres or greater, roughly 66% are less than 500 acres, 12% are between 500 and 1000 acres, and 22% are greater than 1000 acres. Fire exposure is most frequent in the West and Southeast. The years in the sample with the most fires were 2008 and 2012. In-utero fire exposure is highest among births in August to November.

Figure A1: **Characteristics of In-Utero Smoke $PM_{2.5}$ 2007-2017**

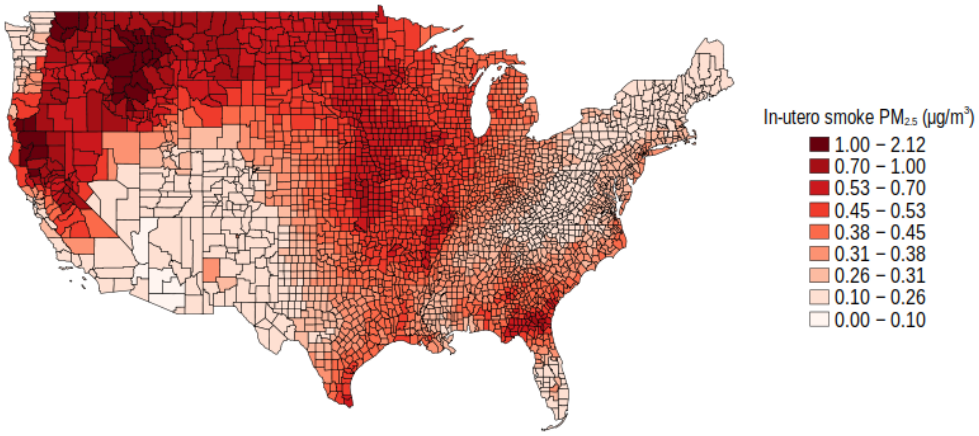
(a) *Histogram*



(b) *Time trend*



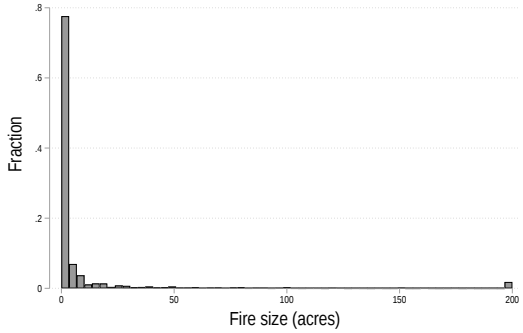
(c) *Spatial distribution*



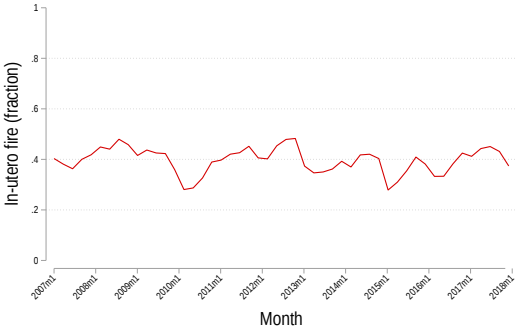
Notes: Panel (a) depicts a histogram of in-utero smoke $PM_{2.5}$ with the percent of county-months observed in each corresponding bin weighted by births. Panel (b) shows the birth-weighted national average of in-utero smoke $PM_{2.5}$ by month. Panel (c) shows the average in-utero smoke $PM_{2.5}$ exposure over our sample period by county.

Figure A2: **Characteristics of In-Utero Fire Exposure 2007-2017**

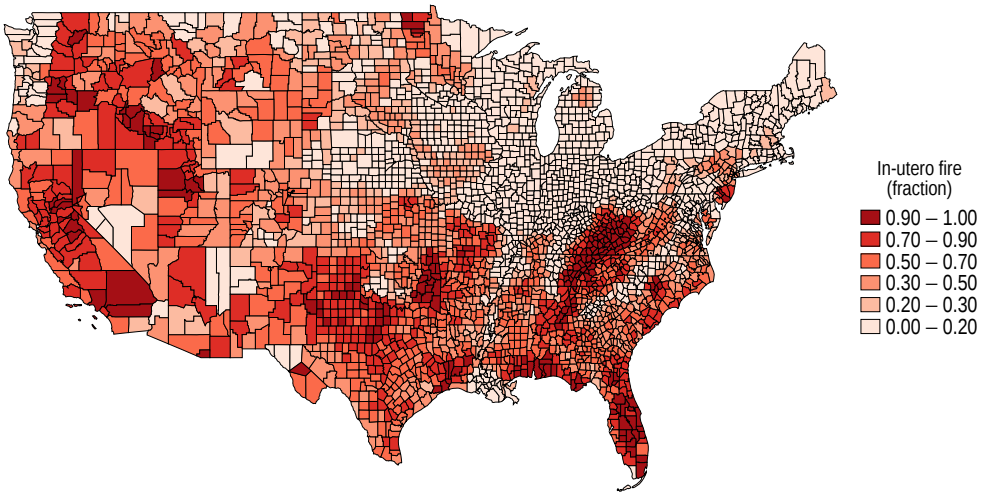
(a) *Histogram - Fire size*



(b) *Time trend - In-utero fire (fraction)*



(c) *Spatial distribution - In-utero fire (fraction)*

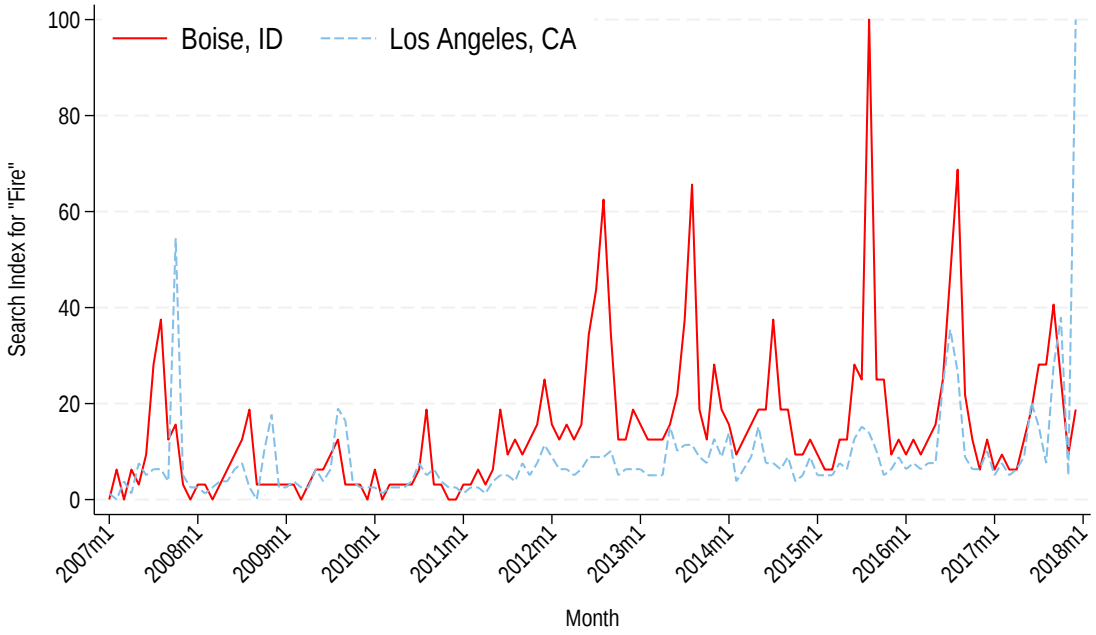


Notes: Panel (a) depicts a histogram of fire size for fires between 2006 and 2018. Fire size is capped at 200 acres. Panel (b) shows the birth-weighted national average of county-months that experienced in-utero fires over our sample period. Panel (c) shows the mean fraction of births that experienced in-utero fires by county.

A.2 Google Trends Data Description

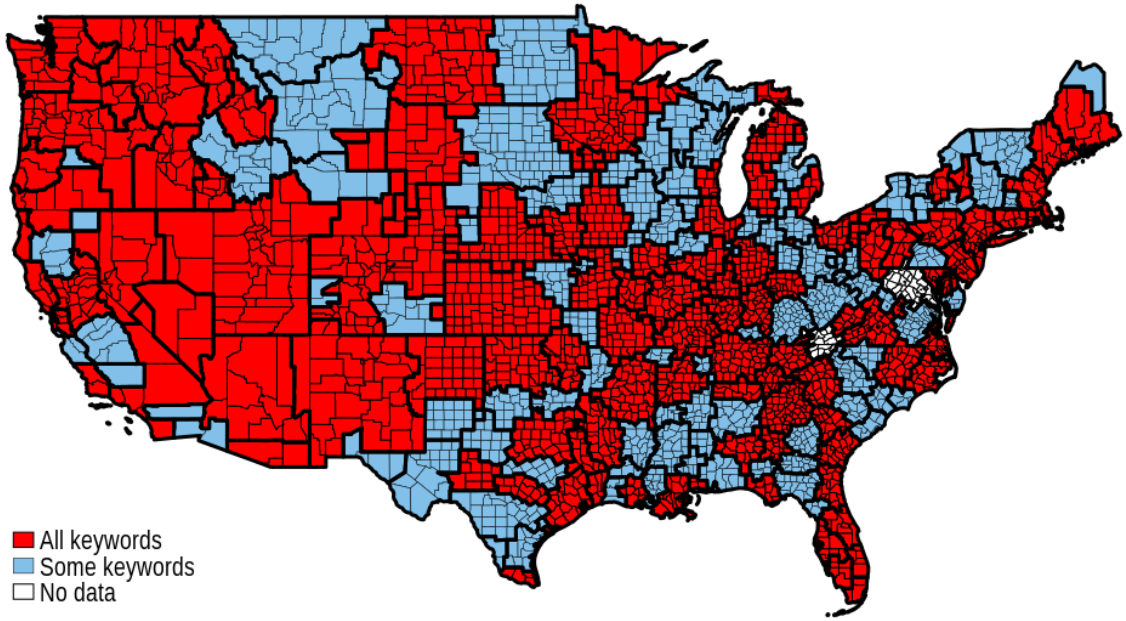
We download DMA-year-month level Google searches for January 2006 through December 2017 for keywords fire, wildfire, smoke, air quality, air purifier, and N95 mask. The data provide an index from zero to 100 where 100 is the maximum search interest over the panel for the queried term and location. Figure A3 illustrates the raw data for two example locations: Boise, ID and Los Angeles, CA. Although there are 206 DMAs in the continental US, data was not available certain terms and DMAs. As a result, for each keyword there is a different set of DMAs that form a balanced panel of DMA-month data. The resulting sample is depicted in Figure A4. We use the crosswalk of US counties to Google's DMAs from Schneider (2025). We collapse our county-year-month panel to DMA-year-month panel using the birth-weighted mean of county-level covariates within the DMA.

Figure A3: **Examples of Google Search Data**



Notes: The unit of observation is the DMA-year-month. Figure depicts the Google trends search index for "fire" in Los Angeles, CA and Boise, ID.

Figure A4: **Geographic Availability of Google Search Data**



Notes: Map shows counties (thin outline) within DMAs (bold outline). Counties are classified by whether Google trends data was available for all keywords, some keywords only, and no keywords.

B Additional Results and Robustness

B.1 Overall Magnitude

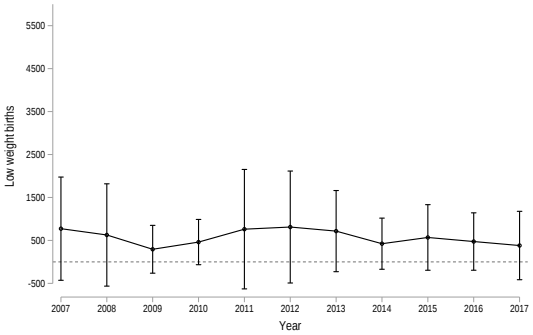
Table A1: **Comparison of Marginal Effects of $PM_{2.5}$ on Rate of Low Weight Births**

Source (study)	% Δ LBW from 1 μgm^{-3} $PM_{2.5}$	Notes
E-ZPass (Currie and Walker, 2011)	6.4	Introduction of E-ZPass reduced incidence of low weight births 9.3% (p. 81). As there are no estimates of the effect of E-ZPass on $PM_{2.5}$, we assume EZ-Pass reduced ambient $PM_{2.5}$ 10.8%, which was roughly the effect on NO_2 (p.85). We assume the level of ambient $PM_{2.5}$ was 13.5 μgm^{-3}, which is midpoint of 2003 New Jersey air quality monitors.
Diesel (Alexander and Schwandt, 2022)	7.3	Cheating diesel increases rate of low weight births 1.9% (p.2892) and $PM_{2.5}$ 0.26 μgm^{-3} (p. 2890).
High sulfur fuel oil (Hansen-Lewis and Marcus, 2025)	4.4	A one μgm^{-3} increase in $PM_{2.5}$ leads to 2.7 additional low birth weight infants per 1,000, or a 4.4 percent increase relative to the mean (p.58).
Wildfire smoke	1.2	A one μgm^{-3} increase in smoke $PM_{2.5}$ lowered rate of low birth weight 0.76 per 1,000 for births without a wildfire within 50 km with relative to mean of 63.5 per 1,000.

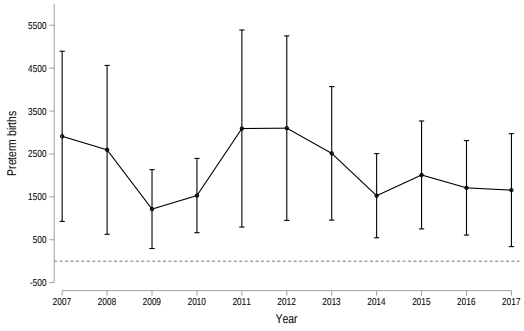
Notes: Table provides the percent change in the rate of low birth weight births per one μgm^{-3} increase in $PM_{2.5}$ for varying sources: E-ZPass toll plazas (row 1), diesel emissions (row 2), high sulfur fuel oil from maritime traffic (row 3), and wildfire smoke (row 4). Explanation of calculations is provided in the notes. New Jersey air quality data from New Jersey Department of Environmental Protection (2003). Source of calculations also draw on Alexander and Schwandt (2022) and Hansen-Lewis and Marcus (2025).

Figure A5: **Additional Low Weight and Preterm Births from Smoke $PM_{2.5}$**

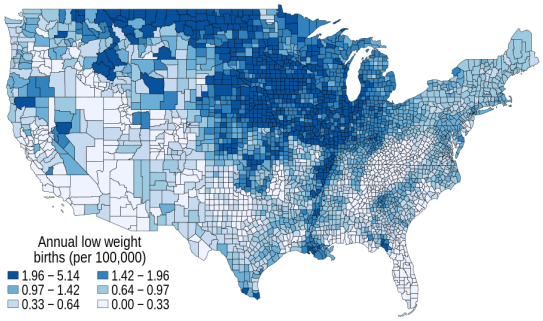
(a) *Average low birth weight births by year*



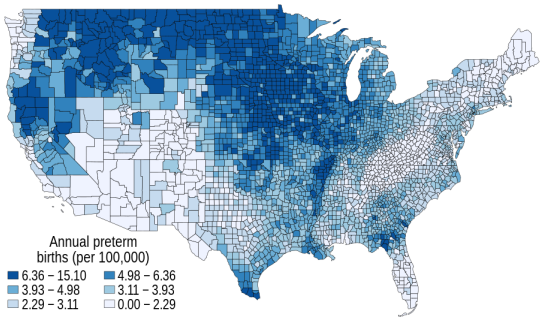
(b) *Average preterm births by year*



(c) *Average low birth weight births by county*



(d) *Average preterm births by county*



Notes: In panels (a) and (b), the figure shows estimated additional low weight births and preterm births per year in the continental United States attributable to wildfire smoke. The confidence intervals are $\pm$ 1.96 standard errors. In panels (c) and (d), the figure shows the estimated annual average additional low weight births and preterm births attributable to wildfire smoke per 100,000 women aged 15-44 years old for each county in the continental United States. See text for details.

B.2 Robustness

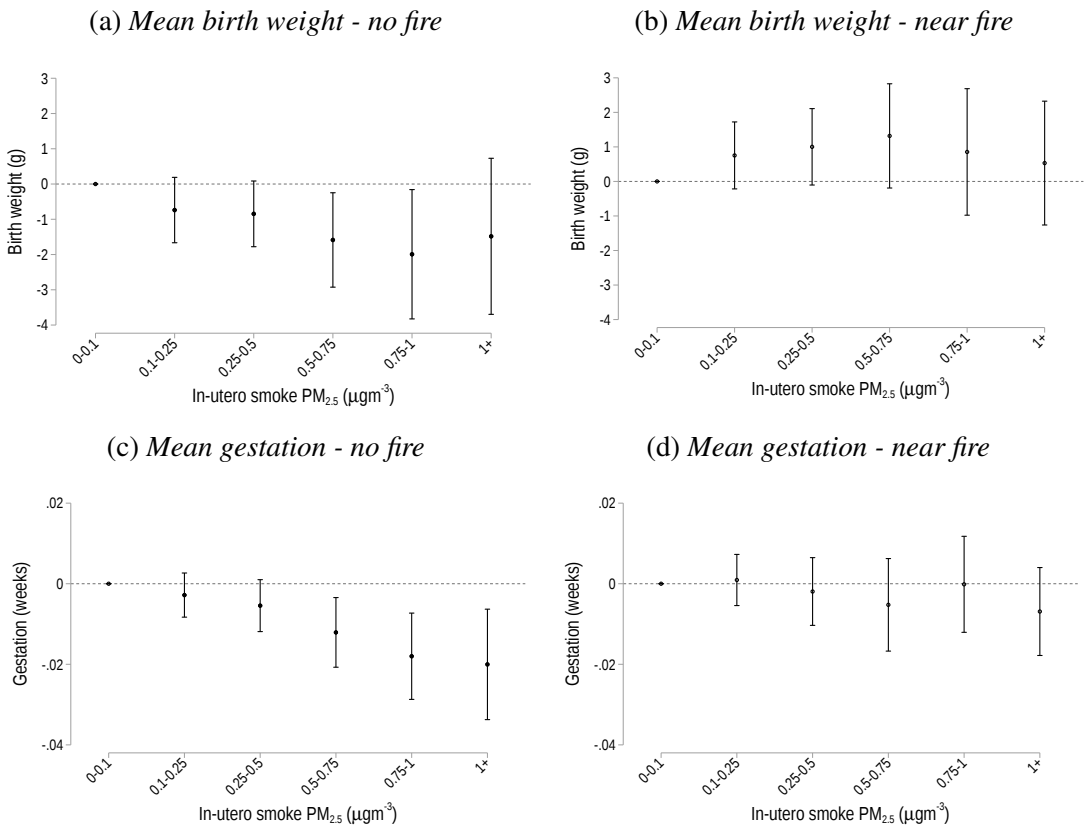
Table A2: **Robustness**

	Low Birth Weight		Preterm		
	(1)	(2)	(3)	(4)	(5)
	$PM_{2.5}$	$PM_{2.5}$*fire	$PM_{2.5}$	$PM_{2.5}$*fire	N clusters
(1) Baseline	0.76	-0.74	2.14	-1.03	3,109
	(0.26)	(0.23)	(0.43)	(0.39)	
(2) Basic FEs	1.24	-0.99	1.89	-1.25	3,109
	(0.26)	(0.24)	(0.48)	(0.45)	
(3) State-month FEs	0.55	-0.61	1.66	-0.94	3,109
	(0.26)	(0.24)	(0.43)	(0.41)	
(4) State-year FEs	0.52	-0.64	1.37	-0.82	3,109
	(0.27)	(0.24)	(0.40)	(0.40)	
(5) Flexible weather bins	0.41	-0.66	1.39	-0.83	3,109
	(0.26)	(0.23)	(0.45)	(0.38)	
(6) Days with smoke	0.02	-0.01	0.03	-0.01	3,109
	(0.00)	(0.00)	(0.01)	(0.01)	
(7) 200 acre fires	0.78	-0.83	2.26	-1.29	3,109
	(0.24)	(0.23)	(0.42)	(0.39)	
(8) 500 acre fires	0.56	-0.61	1.88	-0.90	3,109
	(0.24)	(0.23)	(0.37)	(0.40)	
(9) Fires with containment date	0.71	-0.85	2.24	-1.46	3,109
	(0.21)	(0.21)	(0.39)	(0.39)	
(10) Fires in past 6 months	0.43	-0.36	1.76	-0.61	3,109
	(0.23)	(0.22)	(0.38)	(0.35)	
(11) State-level clustering	0.76	-0.74	2.14	-1.03	49
	(0.32)	(0.27)	(0.49)	(0.45)	

Notes: Estimates are obtained from Equation 1 with outcomes rate of low weight births per 1,000 (columns 1-2) and rate of preterm births per 1,000 (columns 3-4). Column 5 reports the number of clusters in each specification. Unless otherwise noted, standard errors clustered at the county level are reported in parentheses. Row 1 replicates the baseline results of Table 2 columns 2 and 4. Row 2 replaces county-season and region-year fixed effects with county fixed effects. Row 3 replaces county-season and region-year fixed effects with county and state-month fixed effects. Row 4 replaces region-year fixed effects with state-year fixed effects. Row 5 includes more flexible binned weather controls in lieu of the baseline weather controls. For each daily weather variable (minimum temperature, maximum temperature, and precipitation), we include 6 bins: below the 10th percentile, 10-30th percentile, 30-50th percentile, 50-70th percentile, 70-90th percentile, and above the 90th percentile. Row 6 reports the effect of the count of days during the 9 months prior to birth during which there was any smoke over the county of the mother's residence. Rows 7 and 8 define exposure to a fire as the mother residing within 50 kilometers of a fire that burned at least 200 acres (row 7) and 500 acres (row 8). Row 9 limits the exposure to only fires that included a containment date. Row 10 limits the exposure to only fires in the 6 months prior to birth. Row 11 clusters the standard errors at the state-level.

B.3 Nonlinear Effects

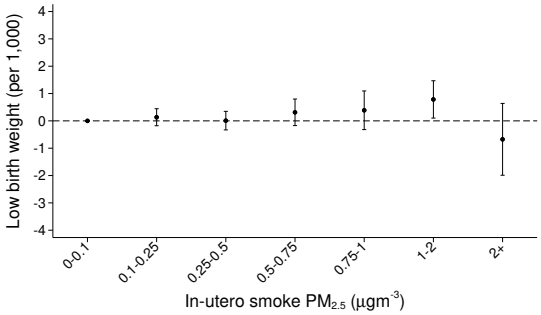
Figure A6: **Nonlinear Effects of Smoke $PM_{2.5}$ on Birth Weight and Gestation Length**



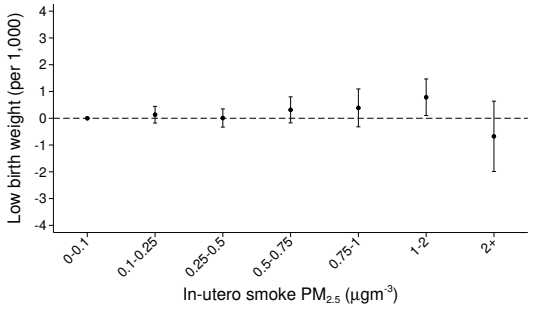
Notes: Estimated coefficients for nonlinear effects of smoke broken down by proximity to a fire. An observation is considered near fire if there was a fire of 100 acres or more within 50 km of the population-weighted county centroid from t to $t-8$ inclusive. Estimates obtained from equation 2. Panels (a) and (b) depict effects on birth weight in grams and panels (c) and (d) depict effects on gestational length in weeks.

Figure A7: **Nonlinear Effects of Smoke $PM_{2.5}$ on Low Birth Weight and Preterm Birth for $PM_{2.5} > 2$**

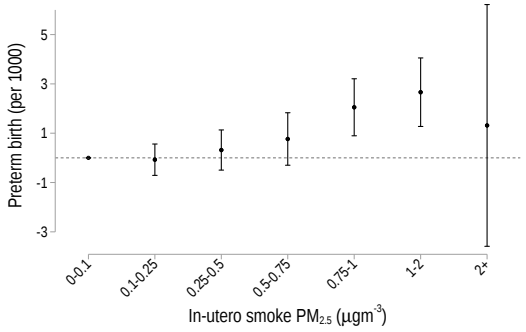
(a) *Low birth weight - no fire*



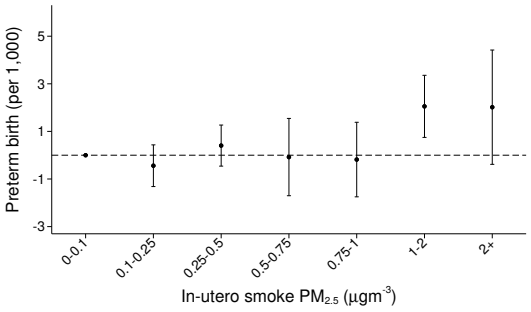
(b) *Low birth weight - near fire*



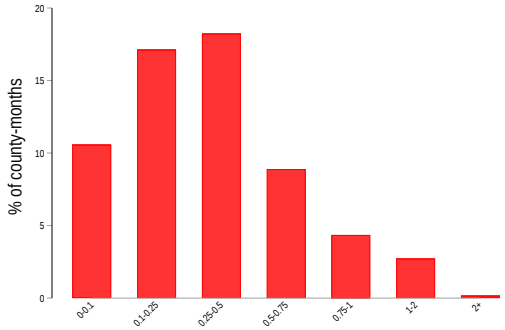
(c) *Preterm - no fire*



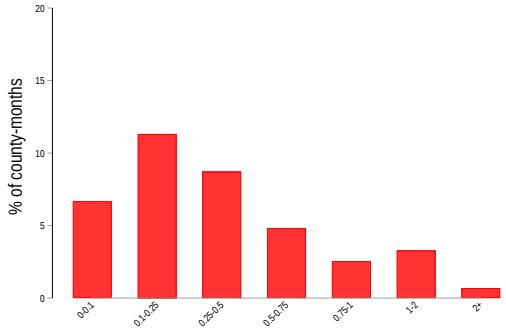
(d) *Preterm - near fire*



(e) *In-utero smoke PM2.5 - no fire*



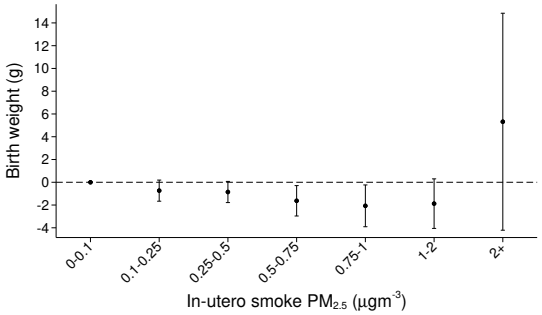
(f) *In-utero smoke PM2.5 - near fire*



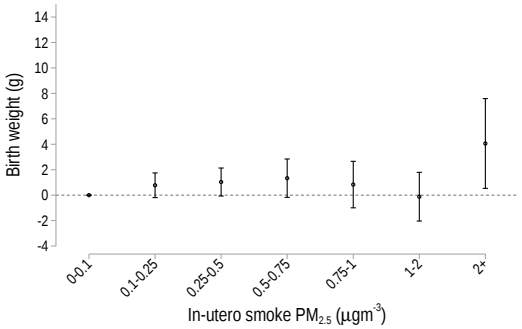
Notes: Estimated coefficients for nonlinear effects of smoke broken down by proximity to a fire. An observation is considered near fire if there was a fire of 100 acres or more within 50 km of the population-weighted county centroid from t to $t-8$ inclusive. Estimates obtained from equation 2 with bins up to 2 μgm^{-3} as depicted. Panels (a) and (b) depict effects on the rate of low weight births per 1,000, panels (c) and (d) depict effects on the rate of preterm births per 1,000, and panels (e) and (f) provide the birth-weighted percentage of county-months that fall within the specified bin.

Figure A8: **Nonlinear Effects of Smoke $PM_{2.5}$ on Birth Weight and Gestation Length for $PM_{2.5} > 2$**

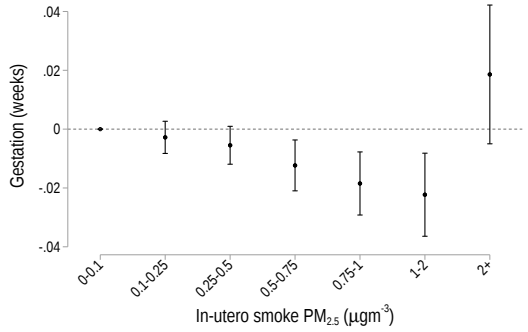
(a) *Mean birth weight - no fire*



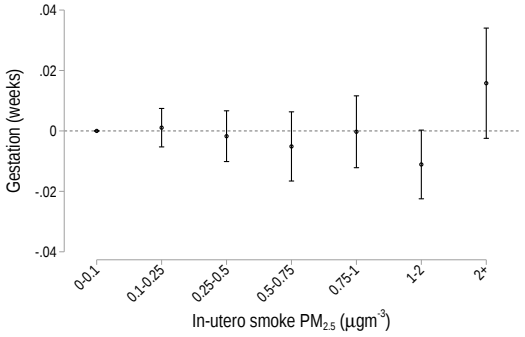
(b) *Mean birth weight - near fire*



(c) *Mean gestation - no fire*



(d) *Mean gestation - near fire*



Notes: Estimated coefficients for nonlinear effects of smoke broken down by proximity to a fire. An observation is considered near fire if there was a fire of 100 acres or more within 50 km of the population-weighted county centroid from t to $t-8$ inclusive. Estimates obtained from equation 2 with bins up to 2 μgm^{-3} as depicted. Panels (a) and (b) depict effects on birth weight in grams and panels (c) and (d) depict effects on gestational length in weeks.

B.4 Additional Outcomes

Table A3: **Effects of In-Utero Smoke on Demographics and Rate of Healthy Births**

	(1) Demog. Index	(2) Unemp. rate	(3) FR	(4) Nlbw/w	(5) Npreterm/w
In-utero smoke $PM_{2.5}$	-0.229	0.048	-0.038	-0.040	-0.044
	(0.361)	(0.040)	(0.012)***	(0.011)***	(0.011)***
In-utero smoke $PM_{2.5}$ * fire	0.083	-0.035	0.017	0.020	0.021
	(0.325)	(0.034)	(0.009)**	(0.008)**	(0.008)***
R^2	0.90	0.91	0.69	0.68	0.66
N	403,064	403,064	403,064	403,064	403,064
N-counties	3109	3109	3109	3109	3109
Mean	3300.89	6.86	4.94	4.63	4.45
%Change β_1	-0.002	0.238	-0.252	-0.284	-0.330
%Change $\beta_1 + \beta_2$	-0.002	0.065	-0.142	-0.144	-0.180
Controls					
Region-by-year FE	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes
County-by-quarter FE	Yes	Yes	Yes	Yes	Yes
X_{imy}	Yes	Yes	Yes	Yes	Yes

Notes: The unit of observation is the county-year-month. The sample includes counties in the continental United States from 2007-2017. The observations are weighted by the number of births in county i in year-month t in columns 1-2 and the number of women of reproductive age in columns 3-5. Estimates are obtained from equation 1. The independent variables are the mean smoke $PM_{2.5}$ from t to t-*8* and its interaction with an indicator of whether there was a fire of 100 acres or more within 50 km of the population-weighted centroid of i from t to t-*8*. The dependent variables are an index of maternal characteristics, including education, marital status, race, ethnicity, age, smoking status, and diabetes (column 1), unemployment rate per 1,000 (column 2), fertility rate per 1,000 women of reproductive age (column 3), rate of not low birth weight births per 1,000 women of reproductive age (column 4), and rate of not preterm births per 1,000 women of reproductive age (column 5). Robust standard errors clustered at the county level are reported in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A4: **Heterogeneity in Effects of Smoke by Education**

	(1) Birth weight	(2) Low birth weight	(3) Gestation	(4) Preterm
In-utero smoke $PM_{2.5}$	-13.113	2.258	-0.003	3.458
	(2.762)***	(0.742)***	(0.010)	(1.009)***
In-utero smoke $PM_{2.5}$ * fire	13.026	-2.573	0.008	-2.714
	(2.863)***	(0.752)***	(0.010)	(0.963)***
In-utero smoke $PM_{2.5}$ * $\geq$ HS ed.	14.360	-1.924	-0.016	-1.711
	(3.382)***	(0.814)**	(0.011)	(1.135)
In-utero smoke $PM_{2.5}$ * $\geq$ HS ed.* fire	-12.791	2.263	0.010	2.092
	(3.526)***	(0.904)**	(0.011)	(1.145)*
R^2	0.04	0.01	0.02	0.01
N	40,773,257	40,773,257	40,773,257	40,773,257
N-counties	3109	3109	3109	3109
Mean	3300.89	63.37	38.73	100.36
Controls	Yes	Yes	Yes	Yes
Region-by-year FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
County-by-quarter FE	Yes	Yes	Yes	Yes
X_{imy}	Yes	Yes	Yes	Yes
No fire, no HS ed.	-13.113	2.258	-0.003	3.458
Near fire, no HS ed.	-0.087	-0.315	0.005	0.744
No fire, with HS ed.	1.247	0.334	-0.019	1.747
Near fire, with HS ed.	1.482	0.024	-0.001	1.126

Notes: The unit of observation is individual-year-month. The sample includes births in counties in the continental United States from 2007-2017. The independent variables are the mean smoke $PM_{2.5}$ from t to t-*8* and its interaction with an indicator of whether there was a fire of 100 acres or more within 50 km of the population-weighted centroid of i from t to t-*8* and these terms interacted with an indicator for whether mother's education was higher than or equal to high school. The dependent variables are average birth weight in grams (column 1), rate of births less than 2,500 grams per 1,000 (column 2), average gestational age in weeks (column 3), and rate of births less than 37 weeks gestation per 1,000 (column 4). Robust standard errors clustered at the county level are reported in parentheses: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.