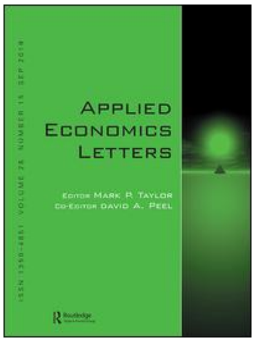

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Wildfire and infant health: a geospatial approach to estimating the health impacts of wildfire smoke exposure

Shawn J. Mccoy[a] and Xiaoxi Zhao[b]

[a]Department of Economics, University of Nevada, Las Vegas, Las Vegas, NV, USA; [b]Department of Economics, University of Pittsburgh, Pittsburgh, PA, USA

ABSTRACT
We estimate the effects of wildfire smoke exposure on infant health. Exposure to wildfire smoke is determined using the latitude and longitude coordinates corresponding to each infant's home address and a fine-scaled spatial dataset of wildfire smoke plumes constructed in GIS from satellite images of the landscape. Using a difference-in-differences estimation strategy, model estimates show that exposure to wildfire smoke leads to a .034 increase in the probability of low birthweight.

KEYWORDS
Wildfire Smoke; Infant Health; Geographic Information Systems

JEL CLASSIFICATION
Q53; Q54; I12; I18

I. Introduction

We investigate the public health implications of wildfire by estimating the impact of wildfire smoke exposure on birthweight and the probability of low birthweight using a spatial dataset of wildfire smoke plumes and the exact locations of infants. Birthweight is a useful outcome to consider since it has been shown to be linked to short-term health outcomes such as one-year mortality rates as well as longer-term outcomes such as educational attainment and earnings (Almond and Currie 2011; Black, Devereux, and Salvanes 2007). Elevated concentrations of fine particulate matter ($PM_{2.5}$)are often considered to be a major threat of wildfire to public health; however, research on the infant health implications of fire is limited. While the physiological pathway between smoke exposure and birthweight remains unclear, researchers hypothesize that after inhalation, the particles and toxicants contained in wildfire smoke cross through the placenta, disrupting foetal nutrition and oxygen flow leading to foetal growth retardation (Jayachandran 2009).

Using a difference-in-differences estimation framework, we compare the health outcomes of infants located inside wildfire smoke plumes to the outcomes of infants located outside the path of smoke. To operationalize this strategy, we digitize smoke plumes in GIS using daily satellite imagery of the terrain. We link this data to a confidential database detailing the health outcomes of infants born in Colorado using the latitude and longitude co-ordinates corresponding to the home address of each infant's mother.

This paper contributes to the growing literature on the health implications of fire. Most closely related to our work, Holstius et al. (2012) study the 2003 wildfires in Southern California by comparing the birthweights of infants located in the South Coast Air Basin (SoCAB) – the portion of the landscape primarily affected by the fires – before and after the fires. Holstius et al. (2012) conclude that infants in the SoCAB experienced an average reduction in birthweight between 3.3 g and 7.0 g. Our work differs from this study in two notable ways. First, the authors do not utilize data delineating the actual path of wildfire smoke. Instead, the authors proxy for smoke exposure by restricting attention to mothers residing in the SoCAB. Second, by estimating a model of first-differences, Holstius et al. (2012) do not leverage the conditionally random nature of wildfires; without data from a valid control group it is difficult to interpret the effects they report as causal. Rangel and Vogl (2016) study agricultural fires in the Brazilian state of Sao Paulo. Using data indicating the locations of fires and information on the municipality of infants' residences, Rangel and

CONTACT Shawn J. Mccoy shawn.mccoy@unlv.edu Department of Economics, University of Nevada, Las Vegas, 4505 S Maryland Pkwy, Box 6005, Las Vegas, NV 89154, USA

Vogl (2016) estimate that an additional upwind fire per week reduces birthweight by 23 g and increases the incidence of low birthweight by 10%.[1]

II. Material and methods

We study wildfire in the state of Colorado between the years 2007 and 2013. Spatial data delineating the locations of fires were obtained from the Geospatial Multi-Agency Coordination Group (GeoMAC) and Monitoring Trends in Burn Severity (MTBS).[2] Fire ignition dates were obtained from each fire's Incident Status Summary (ICS-209) report.[3] We re-construct wildfire smoke plumes in GIS using daily satellite images of Colorado obtained from the University of Wisconsin-Madison Space Science and Engineering Centre.[4] We overlay eight satellite images for each fire – four images from the Terra satellite and four images from the Aqua satellite taken on each of the first 4 days following the ignition of each fire – and digitize the spatial extent of visible smoke in GIS.[5] The final spatial dataset which delineates wildfire smoke plumes for 28 wildfires in Colorado is illustrated in Figure (1).[6]

Vital statistics and natality records for every infant born in the state of Colorado between 2007 and 2013 located within 20 miles[7] of a fire burn and fire smoke plume were obtained under a confidential data agreement with the Centre for Health and Environmental Data at the Colorado Department of Public Health and Environment. These data include information on the birthweight and gestational age of each infant, demographic information for each infant's mother (race, education level, marital status, and age), and the latitude and longitude coordinates associated with each mother's home address. We consider two health outcomes of interest. First, *I(Low Birthweight)* is a binary variable equal to one for any infant with a birthweight less than 2500 g. Second, *Log Birthweight* represents the natural log of each infant's birthweight in grams. Descriptive statistics are provided in Table 1.

For each infant i we identify the nearest fire $m \in M$ that occurred within plus or minus 42 weeks of infant i's birth date.[8] Our baseline empirical specification takes the form:

$$y_{itm} = \alpha \cdot Post_{itm} + \beta \cdot Smoke_{im} \times Post_{itm} + \gamma^m \cdot Treat_{im} + Z_i^{'}\omega_1 + G_{it}^{'}\omega_2 + \tau_{it} + \in_{itm}. \tag{1}$$

$Post_{itm}$ is a binary variable equal to one for any infant conceived[9] before a fire, but born after and zero for any infant conceived and born before. $Smoke_{im}$ is a treatment group indicator equal to one for any infant located inside a wildfire smoke plume and zero otherwise. We include a full set of treatment group by fire fixed effects, $\gamma^m \cdot Treat_{im}$. $Z_i^{'}$ is a vector of demographic controls which includes: an indicator variable for mothers' marital status; indicator variables for mothers' race and education level; and a linear control for mothers' age. τ_{it} is a set of year by month fixed effects and fire by treatment group linear time trends. Finally, $G_i^{'}$ is a vector of landscape controls including elevation, distance to fire, the interaction of elevation and distance, and zip code fixed effects.

We also present estimates based on the strategy proposed by Currie and Rossin-Slater (2013) by decomposing $Post_{itm}$ into three separate indicator variables, $\{Tri_{k,itm}\}_{k=1}^{3}$, indicating the specific trimester[10] each infant was exposed to fire while in-utero:

$$y_{itm} = \sum_{k=1}^{3}\left(\alpha^k \cdot Tri_{k,itm} + \beta_k \cdot Smoke_{im} \times Tri_{k,itm}\right) + \gamma^m \cdot Smoke_{im} + Z_i^{'}\omega_1 + G_{it}^{'}\omega_2 + \tau_{it} + \in_{itm}. \tag{2}$$

[1]Please see Appendix A.1 for a discussion of related works.
[2]http://www.geomac.gov/index.shtml. MTBS: http://www.mtbs.gov/.
[3]http://www.nifc.gov/.
[4]http://www.ssec.wisc.edu/.
[5]Please see Appendix A.2 for a discussion of alternative data sources and the limitations of our methodology.
[6]Please see Appendix A.3 for more details regarding the data utilized in our study.
[7]As shown in Table A1, our model estimates are qualitatively unaffected by this sampling restriction.
[8]Infants with a gestational age greater than 42 weeks are dropped (16 observations).
[9]We use each infant's birth date and gestational age to determine each infant's conception date. Please refer to Currie and Rossin-Slater (2013) for a detailed discussion of the importance of this classification strategy.
[10]Like Currie and Rossin-Slater (2013), we compute trimester of exposure by counting forward from conception dates to fire dates.

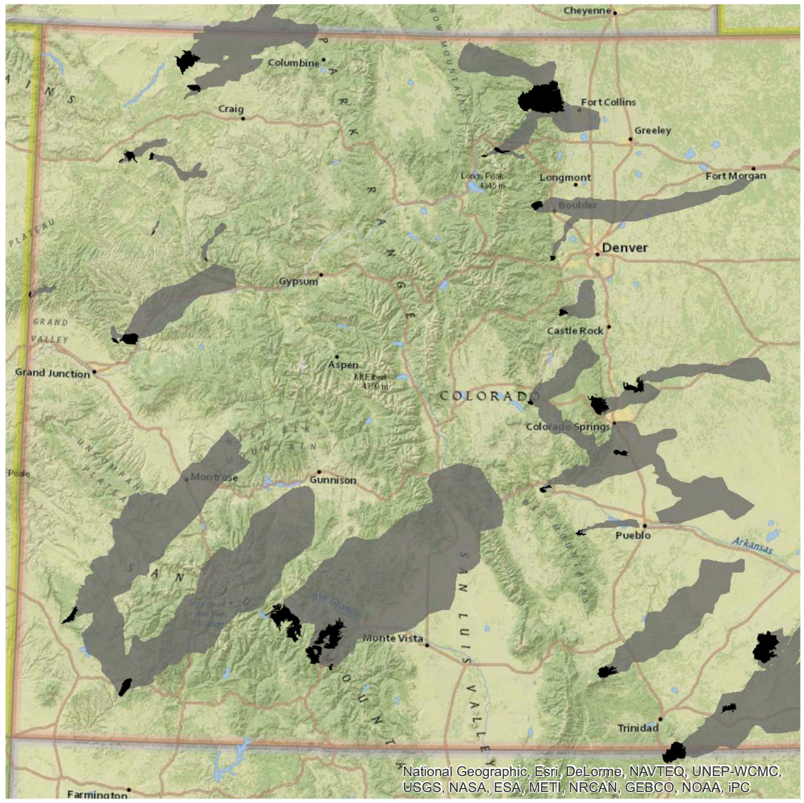

Figure 1. Illustration of the study area: wildfires are depicted in black. Smoke plumes are depicted in dark grey. (Note: Figure intended to be printed in colour).

Of interest to us are coefficient estimates of $\{\beta_k\}_{k=1}^{3}$ which identify average changes in the incidence of low birthweight among infants in the treatment group exposed to fire during their k^{th} trimester relative to changes in the control group. In each model, we cluster standard errors at the zip code level.

Table 1. Descriptive Statistics.

Variables:	Mean	Standard Deviation
I(Low Birthweight)	0.08	0.28
Log Birthweight	8.05	0.21
Smoke	0.11	0.31
Post	0.51	0.50
Tri 1	0.14	0.35
Tri 2	0.22	0.41
Tri 3	0.15	0.36
Mother's Age (Years)	28.46	6.01
I(Married)	0.74	0.44
I(White)	0.63	0.48
I(Black)	0.04	0.19
I(Hispanic)	0.26	0.44
I(Race - Other)	0.07	0.25
I(Master's degree)	0.01	0.10
I(Bachelor's degree)	0.03	0.17
I(Associate's degree)	0.10	0.30
I(Some college, but no degree)	0.30	0.46
I(High school graduate or GED)	0.41	0.49
I(9th to 12th grade, but no diploma)	0.12	0.32
I(8th grade or less)	0.03	0.17
Elevation (meters)	1812.81	250.28
Distance to fire (miles)	12.01	4.65

Notes: Number of observations: 90.779.

III. Results

Table (2) presents coefficient estimates of models 1 and 2. The estimate of Smoke x Post indicates that exposure to wildfire smoke results, on average, in a statistically significant .034 increase in the probability of low birthweight. Turning attention to model 2, coefficient estimates show that the impact of wildfire smoke appears to have a potentially larger effect on infants exposed in their first or second trimester of gestation (Smoke x Tri 1 = .067 and Smoke x Tri 2 = .049); however, formal tests of the difference of these coefficients with the coefficient estimate of Smoke x Tri 3 indicate that these effects are not statistically different (p = .124 and p = .39, respectively). Identification of the causal effect of smoke exposure relies on the assumption that the treatment and the control group would have exhibited similar trends in the absence of treatment. To

Table 2. Model estimates of the impact of wildfire smoke exposure on the incidence of low birthweight.

DV = I(low birthweight)	Coefficient Estimate	Standard Error	95% Confidence Interval
(a) DV = I(low birthweight)			
Smoke x Post	0.0341	0.0146	[0.0055, 0.0627]
(b) DV = I(low birthweight)			
Smoke x Tri 1	0.0674	0.0266	[0.0153, 0.1195]
Smoke x Tri 2	0.0494	0.0208	[0.0086, 0.0902]
Smoke x Tri 3	0.0361	0.0141	[0.0085, 0.0637]
(c) DV = I(low birthweight)			
Days x Smoke	−0.00007	0.00005	[−0.0002, 0.00002]

Notes: Panels (a) and (b) report separate estimates of Equations (1) and (2) with DV = I(low birthweight) as the dependent variable (N = 90,779). Panel (c) reports the coefficient estimate of the interaction term of time since fire (measured in days) and the treatment group indicator on the sample of N = 44,897 pre-fire births. The P-values corresponding to tests for the differences of the coefficients between Smoke x Tri 1 and Smoke x Tri 3 as well as Smoke x Tri 2 and Smoke x Tri 3 are .124 and .390, respectively. Each model clusters standard errors by zip code.

Table 3. Model estimates of the impact of wildfire smoke exposure on log birthweight.

log(birthweight)	Coefficient Estimate	Standard Error	95% Confidence Interval
(a) log(birthweight)			
Smoke x Post	−0.0396	0.0119	[−0.0629, −0.0163]
(b) log(birthweight)			
Smoke x Tri 1	−0.0506	0.0199	[−0.0896, −0.0116]
Smoke x Tri 2	−0.0480	0.0158	[−0.07897, −0.017]
Smoke x Tri 3	−0.0379	0.0111	[−0.0597, −0.0161]
(c) log(birthweight)			
Days x Smoke	0.00005	0.00003	[−0.00001, 0.00011]

Notes: Panels (a) and (b) report separate estimates of Equations (1) and (2) with log(birthweight) as the dependent variable (N = 90,779). Panel (c) reports the coefficient estimate of the interaction term of time since fire (measured in days) and the treatment group indicator on the sample of N = 44,897 pre-fire births. The P-values corresponding to tests for the differences of the coefficients between Smoke x Tri 1 and Smoke x Tri 3 as well as Smoke x Tri 2 and Smoke x Tri 3 are .397 and .347, respectively. Each model clusters standard errors by zip code.

provide evidence supporting this assumption, we restrict attention to the pre-fire time period and estimate a linear regression model including the interaction effects between time since fire (measured in days) and the treatment group indicator. If the treatment and the control group share similar trends, then the interaction term should not be statistically different from zero. Model 3 in Table 2 reports the estimate of the interaction term which is not statistically different from zero.[11] Lastly, Table 3 reports estimates of models 1 and 2 with log birthweight as the dependent variable. Estimates of model 1 show that wildfire smoke leads to, on average, a statistically significant 3.8% reduction in birthweight.[12]

IV. Concluding remarks

We estimate the impact of wildfire smoke exposure on birthweight using a dataset of wildfire smoke plumes linked to a confidential database detailing the locations of infants in our study area. Model estimates show that exposure to wildfire smoke leads to a statistically significant increase in the probability of low birthweight and a corresponding decrease in birthweight. Our findings complement the earlier literature centred on the public health implications of wildfire. Avenues for fruitful work unexplored in this study are the links between wildfire and longer-term health outcomes.

Disclosure statement

No potential conflict of interest was reported by the authors.

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[11]We also fail to reject the null hypothesis that this coefficient equals zero at the .1 level of significance.
[12]exp(−.0396) − 1 = −.038.

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Appendix

A.1. Related Literature

Going beyond the infant health literature, Jayachandran (2009) explores the effects of the 1997 forest fires in Indonesia on early-life mortality. Likewise, Gan et al. (2017) study the relationship between fire-driven increases in fine particulate matter and cardiopulmonary hospital admissions while Wettstein et al. (2018) estimate the effects of smoke exposure on cardiovascular and cerebrovascular events. Burkhardt et al. (2019) estimate the impact of changes in monthly air pollution and violent crime instrumenting for pollution with satellite-based landscape fire smoke plumes. Lastly, please see Liu et al. (2015) and Reid et al. (2016) for reviews of the literature on the health implications of wildfire smoke exposure.

A.2. Alternative Data Sources and Methodological Limitations

While we reconstruct wildfire smoke plumes in GIS for our study, there exist other data sources describing wildfire smoke plumes including the hazard mapping system by the National Oceanic and Atmospheric Institute (HMS[13]). For a description of these data, please see Schroeder et al. (2008). As noted in Brey and Fisher (2016, page 1289), 'HMS does not differentiate smoke from wildfires, controlled wildland burns, agricultural fires, or any other source of smoke.'

We highlight here four factors that may contribute to exposure misclassification that may influence our model estimates. First, smoke identified in the atmosphere above a location does not necessarily coincide with smoke at the surface (Brey and Fischer 2016). Second, the Terra satellite overpasses are 10:30 local standard time and the Aqua's overpasses are 1:30 local standard time; hence, our smoke plumes may tend to be clustered midday. Third, we simplify the construction of our smoke plumes by investigating images within the first 4 days of a fire. Fourth, in our study, we restrict attention to wildfires igniting within Colorado, but due to the potential for wildfire smoke to travel long-range, residents of Colorado could be potentially exposed the long-range transport of smoke from fires igniting in proximate states.

A.3. Data Appendix

Historical wildfire perimeters were downloaded from GEOMAC (https://www.geomac.gov/) and MTBS (https://www.mtbs.gov/) on 29 September 2014. These datasets[14] in their raw format are

[13]https://www.ospo.noaa.gov/Products/land/hms.html.
[14]The data described in this section can be accessed here: https://tinyurl.com/twya4mc.

titled geomac_9_24_2019.shp and mtbs_9_24_2019.shp. These datasets were loaded in ArcGIS. Any wildfire less than 300 acres was subsequently dropped from each. Any wildfire that did not occur in the state of Colorado was also dropped. To normalize the data with respect to time, wildfires igniting on or before the year 2001 were dropped from both datasets. We use both datasets to create a comprehensive dataset of wildfire perimeters in Colorado. Along these lines, in some cases, we found that there exist wildfires in the GEOMAC data that do not exist in the MTBS data. In other cases, there exist wildfires in the MTBS data that do not exist in the GEOMAC data. In all remaining cases, there exist wildfire polygons in both datasets representing the same fires. To normalize these data, the MTBS and GEOMAC perimeters were loaded into ArcGIS and dissolved into a single Esri Shapefile combining wildfire polygons from each dataset corresponding to the same fire into a single wildfire polygon resulting in the dataset titled dissolved_fires_204.shp. Note that each fire was given a unique numerical identifier labelled ' newid' . The excel spreadsheet titled ' firelist.xlsx' represents a crosswalk between each fire (newid) and the ignition date of each fire (date).

Satellite imagery was subsequently obtained from the University of Wisconsin-Madison Space Science and Engineering Centre. As detailed in the body of the manuscript, for each fire ignition date, we downloaded eight satellite images: four satellite images produced by the Terra satellite corresponding to the first 4 days following the ignition date of said fire and four satellite images produced by the Aqua satellite image corresponding to the first 4 days following the ignition date of each fire. These images were accessed using the MODIS Today interface (http://ge.ssec.wisc.edu/modis-today/). As detailed in the manuscript, we overlay all images for each fire (four images from the Terra satellite and four from the Aqua satellite) and digitize the spatial extent of visible smoke in ArcGIS. At a resolution of 250 m, we were unable to identify the presence of smoke for many of the smaller fires in the sample. In other cases, we were unable to construct plumes due to excessive cloud cover. As a result, it is possible that wildfire exposure is potentially miss-classified for some infant' s in our sample. Specifically, there may be infants in our sample coded as not residing within a smoke plume when they potentially are. The final dataset of wildfire smokes plumes stored as an Esri Shapefile can be accessed from the folder titled 'plumes'. The corresponding dataset describing the burn scars associated with each plume can be accessed from the folder titled 'scars'.

A.4. Robustness Check: Sensitivity of Model Estimates to Sample Definition

Table A1. Sensitivity of model estimates to sample definition.

DV = I(low birthweight)	Coefficient Estimate	Standard Error	95% Confidence Interval	N	Distance to Fire	Distance to Plume
(a) DV = I(low birthweight)						
Smoke x Post	0.0339	0.0144	[0.0057, 0.0621]	158,906	Any	Any
Days x Smoke	−0.00006	0.00004	[−0.0001, 0.00002]	76,692	Any	Any
Smoke x Post	0.0361	0.0146	[0.0075, 0.0647]	91,805	<20 miles	Any
Days x Smoke	−0.00007	0.00005	[−0.0002, 0.00002]	45,135	<20 miles	Any
Smoke x Post	0.0322	0.0144	[0.004, 0.0604]	137,234	Any	<20 miles
Days x Smoke	−0.00007	0.00004	[−0.0002, 0.00002]	66,513	Any	<20 miles
Smoke x Post	0.0341	0.0146	[0.0055, 0.0627]	90,779	<20 miles	<20 miles
Days x Smoke	−0.00007	0.00005	[−0.0002, 0.00002]	44,897	<20 miles	<20 miles
(b) DV = log(birthweight)						
Smoke x Post	−0.0372	0.0112	[−0.0592, −0.0152]	158,906	Any	Any
Days x Smoke	0.00007	0.00003	[0.000004, 0.00013]	76,692	Any	Any
Smoke x Post	−0.0412	0.0120	[−0.0647, −0.0177]	91,805	<20 miles	Any
Days x Smoke	0.00005	0.00003	[−0.000011, 0.00012]	45,135	<20 miles	Any
Smoke x Post	−0.0382	0.0115	[−0.0607, −0.0157]	137,234	Any	<20 miles
Days x Smoke	0.00007	0.00003	[0.000006, 0.00013]	66,513	Any	<20 miles
Smoke x Post	−0.0396	0.0119	[−0.0629, −0.0163]	90,779	<20 miles	<20 miles
Days x Smoke	0.00005	0.00003	[−0.000014, 0.00011]	44,897	<20 miles	<20 miles

Notes: Panels (a) and (b) report coefficent estimates of Smoke x Post obtained from estimation Equation (1) for various sample definitions each constructed based on the distance between each infant and wildfire and each infant and wildfire smoke plume as well as the coefficient estimate of the interaction term of time since fire (measured in days) and the treatment group indicator on the sample pre-fire births. Each model clusters standard errors by zip code.