Wildfire Smoke and Fatal Crashes: Evidence from the American West

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Abstract

This article focuses on the causal impact of forest fire smoke on motor vehicle collisions in the contiguous Western United States. To evaluate this effect, I merged daily wildfire smoke exposure data with the number of car crashes for all counties in the American West. My detailed findings demonstrate the negative impact of smoke on road accidents. I document that a smoke day increases the number of deadly collisions by a 7.1 percent compared to a day without smoke plumes. The adverse effect is mostly observable in the metropolitan areas and adds \$3.7 billion or roughly 0.9 percent in estimated losses from car fatalities annually within the entire United States.

1 Introduction

Motor vehicle traffic accidents lead to tens-of-thousands of fatalities annually and are the second largest cause of accidental deaths among individuals below 45 years old in the United States[1]. Recent estimates indicate tremendous annual societal costs of these crashes totaling $1.4 trillion in 2019, with approximately $412 billion of this cost from fatalities (Blincoe et al., 2023). A deeper understanding of their determinants could help policymakers determine how to best enhance road safety and reduce the enormous costs associated with severe accidents.

One important determinant of deadly traffic collisions is hazardous air quality. Studies show that ambient air pollution can have a detrimental impact on road safety but may also induce more cautious driving. Contaminated air causes cognitive impairment, which in turn limits driving performance and can increase accidents (Mackenzie and Harris, 2017; Sager, 2019; Zhang et al., 2023). The adverse impact of pollution on cognitive abilities can include heightened aggressive behaviour (Schikowski and Altuğ, 2020; Burton and Roach, 2023). Finally, air pollution can worsen road safety by limiting visibility (Intini et al., 2022). However, all of these negative impacts could be mitigated by visibly elevated levels of air pollution inducing more careful driving and/or encouraging some drivers to refrain from non-essential trips (Singh et al., 2021; Shr et al., 2023). As a result, the overall effect of adverse air quality on road safety is uncertain and is likely to vary with the intensity of pollution.

Wildfires are increasingly key contributors to dangerous levels of pollution in the Western United States (American Lung Association, 2024). Smoke plumes from fires are known to travel thousands of miles away from their origins (Miller et al., 2017). In certain regions, such as the western half of the United States, wildfire smoke has significantly slowed multi-decadal progress in ambient air quality improvements in the United States (Burke et al., 2023).

In this paper, I estimate the causal impact of wildfire smoke on road safety in the contiguous Western Unites States[2]. I combine daily counts of fatal injuries sustained in motor vehicle traffic collisions from the Fatality Analysis Reporting System (FARS) from 2011 to 2015 with

[1]The associated chart and data could be found here: https://www.cdc.gov/injury/wisqars/animated-leading-causes.html.

[2]In this study, I consider the following twelve states: Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Texas, Utah, Washington, and Wyoming.

satellite-derived wildfire smoke plume images available through the National Oceanic and Atmospheric Administration's (NOAA) Hazard Mapping System (HMS). The latter data is used to compute several measures of forest fire smoke presence and intensity within counties in the American West. I estimate the effect of various levels of smoke pollution on fatal car accidents using a two-way fixed effects specification that accounts for time-invariant unobserved county characteristics and common temporal shocks, as well as controls for other important determinants of road safety such as daily weather conditions.

I find that exposure to wildfire smoke on a given day increases the number of fatalities in a county by 0.003, which corresponds to a roughly 7.1 percent increase relative to the average number of daily road fatalities within a county in my sample. These magnitudes imply that wildfire smoke causes an extra 292 road fatalities each year, which translates into additional $3.7 billion in estimated losses within the United States annually.

This article contributes to the literature in several important ways. First, estimating the causal impact of air pollution on traffic fatalities is difficult in most contexts because of reverse causality and unobserved confounders that may be correlated with exposure and traffic outcomes. As an example, increases in traffic volume will increase pollution but also could increase the risk of accidents occurring. Moreover, changes in local economic activity can have direct causal impacts on air quality. Variation in air quality due to wildfire smoke is plausibly exogenous given wind can move large distances away from the source locations, generating a set of far-reaching and lasting air quality shocks unrelated to local activity (Sokolik et al., 2019). These characteristics make smoke a useful natural experiment that can be used to better understand the causal impact of air pollution on road safety.

Second, existing studies linking contaminated air to road safety outcomes report mixed results. On one hand, air pollution is associated with lower visibility, worse driving behaviour, cognitive impairment, all which lead to increases in fatal accidents (Sager, 2019; Shi et al., 2022). On the other hand, high air pollution levels encourage cautious driving or road avoidance altogether (Shr et al., 2023). Likely due to these competing mechanisms, some studies fail to find any significant impact of air quality on road safety (Dastoorpoor et al., 2016). A recent paper examining the relationship between poor air quality and fatal vehicle collisions in California finds adverse effects of air pollution on road safety that are mitigated by driver risk aversion (Braun and Villas-Boas, 2024). Variation in the visibility/density of pollution is critical to understand the role of these competing mechanisms which I am able to measure using geo-specific smoke plume intensity data captured by the NOAA satellites.

Third, studies investigating the impact of poor air quality often focus on a few chosen pollutants, such as ozone, particulate matter, or nitrogen oxides (Maji et al., 2023). However, the toxic potency of a pollutant varies by its sources. Wildfires generate a great deal of fine and ultrafine particles which penetrate into the lungs and are transported through the bloodstream which have both short- and long-term health consequences (Aguilera et al., 2021; Zhang et al., 2024). Wildfire smoke plumes also contain other harmful types of pollutants that are frequently omitted in single class pollutant research articles, such as methane, benzene, carbon monoxide and volatile organic compounds (Simmons et al., 2022). But even when individual measures of each air contaminant are readily available, multiple pollutant studies are unable to account for the potential interaction effects between contaminant mixtures, which can exacerbate the health impacts (Yu et al., 2022). All of the contaminants present in fire smoke could potentially amplify health consequences through their chemical interactions[3] (Mainka and Żak, 2022; Liu et al., 2023). Because of these complex relationships between fire smoke and individual contaminants, I focus on measures of smoke presence and intensity since this variation encompasses the diverse set of pollutants.

Finally, a body of literature focuses on the direct effect of big wildfires or other extreme weather events by estimating their economic and health impacts on nearby communities (Kizer, 2020; Kim et al., 2021). While large fires can be detrimental to specific communities, few studies consider the broader impact of air pollution shocks from the drifting smoke plumes. Even prescribed fires can result in large concentrations of particulate matter in the air and adversely affect downwind communities (Jones et al., 2022; Baryshnikova and Wesselbaum, 2023). I use the entire set of fire smoke plumes to provide the most comprehensive study to date with regards to their impacts on road safety.

The rest of the paper is structured as follows. Section 2 outlines data sources. Section

[3]For example, the exposure to $PM_{2.5}$ or NO_2, adjusted for the other pollutant, demonstrates a synergistic effect considering mortality from respiratory diseases.

3 describes the empirical strategy. Section 4 discusses main results, assesses heterogeneous effects, and tests the robustness of my findings. Section 5 provides concluding remarks.

2 Data Sources

2.1 Motor Vehicle Fatalities Data

I use publicly available data tracking fatal injuries suffered in vehicle accidents provided by the Fatality Analysis Reporting System (FARS) in the United States from 2011 to 2015. I focus on the months of March through November since there is very little variation in smoke plume coverage during winter months. The FARS data contains extensive details about all fatal accidents including specific information about each collision, such as the date it occurred, its location, the number of people and vehicles involved, and whether alcohol or other substances were involved. I geocode the location of each accident to the county of occurrence.

2.2 Smoke Plumes and Air Quality Data

The satellite tracking of wildfire smoke plumes is administered by NOAA's Hazard Mapping System (HMS). Smoke experts perform input data quality checks and transform the incoming forest fire smoke identifications into a digital map depicting the expanse of the wildfire smoke and its intensity each day. I use this dataset to calculate the daily smoke coverage and intensity values for each county in the sample. One limitation of this data is that there are no details provided about the elevation of smoke clouds. While smoke plumes higher in the atmosphere may overstate the true exposure at the ground level, several studies document a strong link between fire smoke plume locations and data from air pollution monitors on the ground (Hung et al., 2020; O'Dell et al., 2021; Burke et al., 2023). To establish this connection in my context, I provide estimates of the relationship between my county-level smoke plume data and daily county-level air quality index (AQI) data available from the Unites States Environmental Protection Agency (EPA)[4].

[4]The EPA dataset includes information for approximately 40 percent of county-by-date entries constructed from the FARS data. While the AQI data provides sufficient number of data points for a reasonable examination on the relationship between forest fire smoke and ground-based air pollution, it severely limits the ability to employ instrumental variable approach in this article.

2.3 Other Data

Weather conditions could directly influence deadly road accidents as well as affecting the presence of smoke. As a result, I gather detailed weather information prepared by the NOAA's Climate Data Online database to control for the influence of weather on my outcomes of interest. In my primary specification, I control for average daily temperatures and precipitation amounts for each county in the sample over the analysis period. Importantly, the smoke data depicts the spatial distribution of smoke plumes during the day implying that wind patterns are embedded in this data[5]. My data is further supplemented by the county-level Rural-Urban Continuum Codes managed by the U.S. Department of Agriculture which classifies each county into one of the three categories – a metropolitan, urban, or rural area.

3 Research Methodology

3.1 Forest Fire Smoke Exposure

I use daily variation in the exposure to wildfire smoke across all counties in the American West to examine the causal impact of air pollution events on the number of motor vehicle fatalities. Smoke plumes can drift thousands of miles downwind, naturally separating the effects of smoke exposure from the direct devastation caused by burning fires. Figure 1 illustrates annual frequency and spatial allocation of smoke shocks in my analysis sample. The average county experiences more than a full month of smoke days in a year but this can vary significantly across years. There is also substantial variation across the counties in these Western US States.

The fraction of the area of a representative county that is covered by any smoke plumes is 0.1231 on a typical day in my analysis dataset as outlined in Table 1. In general, heavier smoke episodes occur less frequently than lighter ones. With regard to the number of crashes, there are 0.0385 accidents observed in an average county each day in the estimation sample.

To establish the effect of these smoke plumes on traditional air quality measurements from

[5]Other factors like fog can negatively affect road safety but I am unable to obtain daily historical data tracking these conditions. However, given the fact that fog is typically densest in the early morning when traffic is calm and small influence of other weather conditions on my results, I do not expect the inclusion of more detailed weather data to have a significant impact on my estimates.

ground-based air quality monitors, I regress[6] daily air quality index measures on my measures of smoke plume intensity. Column 1 of Table 2 demonstrates that a smoky day is associated with an elevated AQI (worse air quality) on that day. Moreover, heavier smoke intensities are associated with larger increases in AQI demonstrating a dose-response relationship between my smoke intensity measure and ground-based air quality measures.

3.2 Empirical Design

My research approach leverages daily variation in wildfire smoke coverage across all counties in the contiguous Western United States to estimate the causal impact of smoke on road safety during the months of March through November from 2011 through 2015 using the following regression equation:

$$Y_{cd} = \beta \cdot Smoke_{cd} + X_{cd}\gamma + \alpha_c + \alpha_d + \varepsilon_{cd} \tag{1}$$

The dependent variable, Y_{cd}, denotes the number of fatalities in county c on day d. The main independent variable, $Smoke_{cd}$, measures the fraction of the area of county c that is covered with smoke plumes on a day. In same specifications, I decompose this measure into the three smoke intensity classifications that are available in the data – low, medium, and heavy smoke. X_{cd} is a vector of controls for weather patterns, such as temperature and precipitation, to account for potential correlation with wildfire smoke and direct influence of weather on road safety. The main specification also includes county fixed effects, α_c, to account for unobservable differences between geographic units, and date fixed effects, α_d, that capture region-wide time-invariant daily patterns such as activity level differences by day-of-the-week. All models cluster standard errors at the county level.

For my key coefficient of interest, β, to represent the causal effect of an additional smoke day on the number of traffic fatalities, the variation in my measure of smoke days must be uncorrelated with unobserved determinants of fatalities after conditioning on control variables X_{cd} and time-invariant county and date characteristics captured by α_c and α_d. X_{cd} controls for factors that vary within counties and are likely related to the presence of smoke (e.g.

[6]The regression also includes county together with day fixed effects and consistent with variation used in equation 1 below.

temperature and precipitation). The stability of my estimated impacts across specifications with or without controls, along with a placebo check estimating the impact of future smoke days on contemporaneous outcomes, help to support my causal identification assumption in this setting.

4 Results

4.1 Main Findings

The primary results from estimating equation 1 are reported in Table 2. As observable in column 2 of Panel A, I find that a day with full smoke coverage increases the number of fatalities per county per day by 0.003 compared to a smoke-free day. This represents a rise of 7.1 percent relative to the mean number of deadly car accidents, and corresponds to 292 additional lethal collisions annually nationwide[7]. Panel B demonstrates the detailed breakdown of forest fire smoke effects on the number of fatalities for the three available smoke intensities. The heaviest smoke is unsurprisingly the most dangerous type, yet it is a rare event as observable in Table 1. Importantly, low intensity smoke, which is most prevalent and typically invisible to human eyes, still has statistically and economically significant adverse impact on driving conditions.

Next, I test whether smoke exposure has any longer-term or lagged effects at the daily level (column 3) or weekly aggregates (column 4). The specific choice of lags is motivated by some research that finds that the impact of air pollution on outdoor activities and driving can potentially last for a few days (Graff Zivin and Neidell, 2009; Shi et al., 2022). Interestingly, the negative impacts of smoke are concentrated on the specific day of exposure with no evidence of effects persisting in the next day or the next week. These patterns suggest that any relationship between exposure and persistent cognitive impacts is not detectable in traffic fatalities.

I also estimate my primary specification using alternative outcome measures and report these results in Table 3. Effects on the number of fatal crashes or the number of motor vehicles involved are very similar to my estimates using the number of individual fatalities. The baseline effect of a smoke day in a county corresponds to an increase of 6.8 and 7.6 percent, respectively,

[7]To describe findings at the national level, I implicitly assume that the results from the western states are representative of those from the entire country. Given the annual average number of deadly episodes in the United States of 33,476 over the analysis period, combined with the average number of daily smoke (0.1231), and using the estimated 7.1 percent increase in fatal motor vehicle victims due to forest fire smoke presence, the smoke exposure contributes to the growth in lethal outcomes from collisions of 292 each year or 0.8 per day.

relative to the means of these outcomes. A smoke day increases the total number of people involved in lethal collisions by around 6 percent relative to the mean (column 3 of Table 3). Finally, the number of deadly accidents involving drunk drivers rises by around 9 percent relative to the mean on a smoke day, possibly due to the interaction of reduced cognitive abilities from intoxication and the impacts of the pollution (Han and Jia, 2022). In other words, smoke may exacerbate the dangers associated with driving under the influence.

4.2 Heterogeneous Results

To further understand the link between smoke plumes and road safety, I explore how effects vary by the type of county and the specific day of the week. This exercise illustrates the conditions under which road safety is most sensitive to pollution events. Specifically, I evaluate whether effects are similar across counties designated as metropolitan, urban, or rural; and whether effects are similar on weekdays versus weekends.

The results of this exercise are presented in Table 4. Columns 1 through 3 highlight that the underlying detrimental effect of smoke is predominantly concentrated in metropolitan areas with little impact in less populated counties. Metropolitan areas have denser traffic patterns which could imply that driving errors are more likely to result in fatal accidents.

I find relatively similar impacts of smoke on weekdays and weekends, yielding a 6.6 percent and a 7.6 percent increase in lethal motor vehicle crashes, respectively (columns 4 and 5). However, it is worth noting that I estimate a materially larger impact of heavy smoke during the weekends (column 5, Panel B). An intense smoke day increases the number of fatalities by a 23 percent, which is more than triple the effect on weekdays. Since impaired driving is one of the top contributors to lethal vehicle accidents (Romano and Pollini, 2013), this effect could be linked with the increased alcohol and other recreational drug consumption over the weekends (Lau-Barraco et al., 2016; Buckner et al., 2019) compounding the negative impacts of pollution.

4.3 Robustness of Results

I evaluate the robustness of my results to alternative specifications and present results from a placebo specification in Table 5. It is possible that the main effect of smoke described in the paper is driven by other general trends, such as the possibility of areas experiencing more smoke days also experiencing higher growth in the numbers of drivers. I construct an outcome variable that represents a fatality rate by dividing the number of fatalities by the number of cars registered (I scale by 6 million registrations in the respective state to obtain an outcome mean similar to that used in my baseline dependent variable for comparison). As shown in column 2, the estimated impact of a smoke day in this specification is indistinguishable from the baseline. I also check whether results are similar in a population-weighted specification. Column 3 emphasizes that the wildfire smoke impact contributes to a generally comparable 5 percent increase[8] in tragic accidents under the population-weighted model. Another possible concern is the choice of a linear regression model, since my dependent variable contains many zeroes. A natural alternative is a generalized linear model for count data. Column 4 reports estimates for a Poisson regression. This model also yields a similar magnitude of 8.8 percent increase[9] in car fatalities due to smoke shocks.

Finally, as a placebo check, I estimate the impact of the next day smoke measures on current fatal collisions in column 5. If there were other unobserved determinants of fatal accidents correlated with the timing and location of smoke plumes, I would also expect these factors to be potentially correlated with smoke plumes on the day after. Thus, no significant smoke impacts on the following day detected in column 5 help to support my key causal identification assumptions.

5 Conclusions

Wildfires are devastative natural phenomena that frequently destroy properties and threaten those living in the areas they burn. The resultant wildfire smoke plumes carry many harmful air pollutants that can drift great distances, negatively affecting communities far from the fires. In this paper, I examine daily variation in wildfire smoke and its intensity across the contiguous Western United States and find that forest fire smoke exposure causes statistically and economically meaningful increases in fatal motor vehicle crashes.

My results are able to shed more light on the mechanisms at play and provide a few key

[8]This number is calculated as follows: 0.0204/0.4121*100% = 5%

[9]This number is computed based on the standard interpretation of coefficients from the Poisson regression: $(e^{0.0840} - 1) * 100\% = 8.8\%$.

insights. I find increases in fatal accidents even in the presence of low intensity smoke plumes. This suggests that cognitive impairment plays a key role, since these are days in which it is less likely that drivers would notice the pollution and modify their driving behaviour. Further, my results suggest that the greatest impact on road safety is contemporaneous – on the day of smoke exposure – and does not have longer-lasting effects. Additionally, my research suggests drivers under the influence may be the most susceptible to tragic mistakes, especially during the heavy smoke episodes. Finally, these impacts are heavily concentrated in major metropolitan counties which, perhaps, is surprising given that many likely associate fires and the negative impacts of fires with more rural areas.

The estimated marginal impact of a smoke day stands at a 7.1 percent, while a typical county in my analysis sample is subject to 0.1231 smoke exposure on a given day, resulting into almost 0.9 percent total increase in lethal accidents. Given the average number of fatalities in the entire Unites States over the period of 2011 through 2015 is 33,476 annually or roughly 91.7 each day, the overall effect of forest fire smoke constitutes 0.8 more fatalities daily or 292 annually across the U.S. To put this in perspective using the recent total cost from fatalities of $412 billion per year (Blincoe et al., 2023), the comprehensive impact of wildfire smoke on driving incidents aggregates to $3.7 billion in additional losses each calendar year.

One promising area of future research is to extend the geographic scope of this article by considering the entire United States. This enables more representative estimates of smoke and the respective fatality costs. Next, a comprehensive air pollution data would improve ground-based monitor measures that currently cover less than half of all observations in the analysis sample. Finally, future work could incorporate traffic volume data. Such dataset would allow to distinguish between contrasting mechanisms outlined in this paper. A traffic reduction during intense smoke days could indicate avoidance behaviour among road users.

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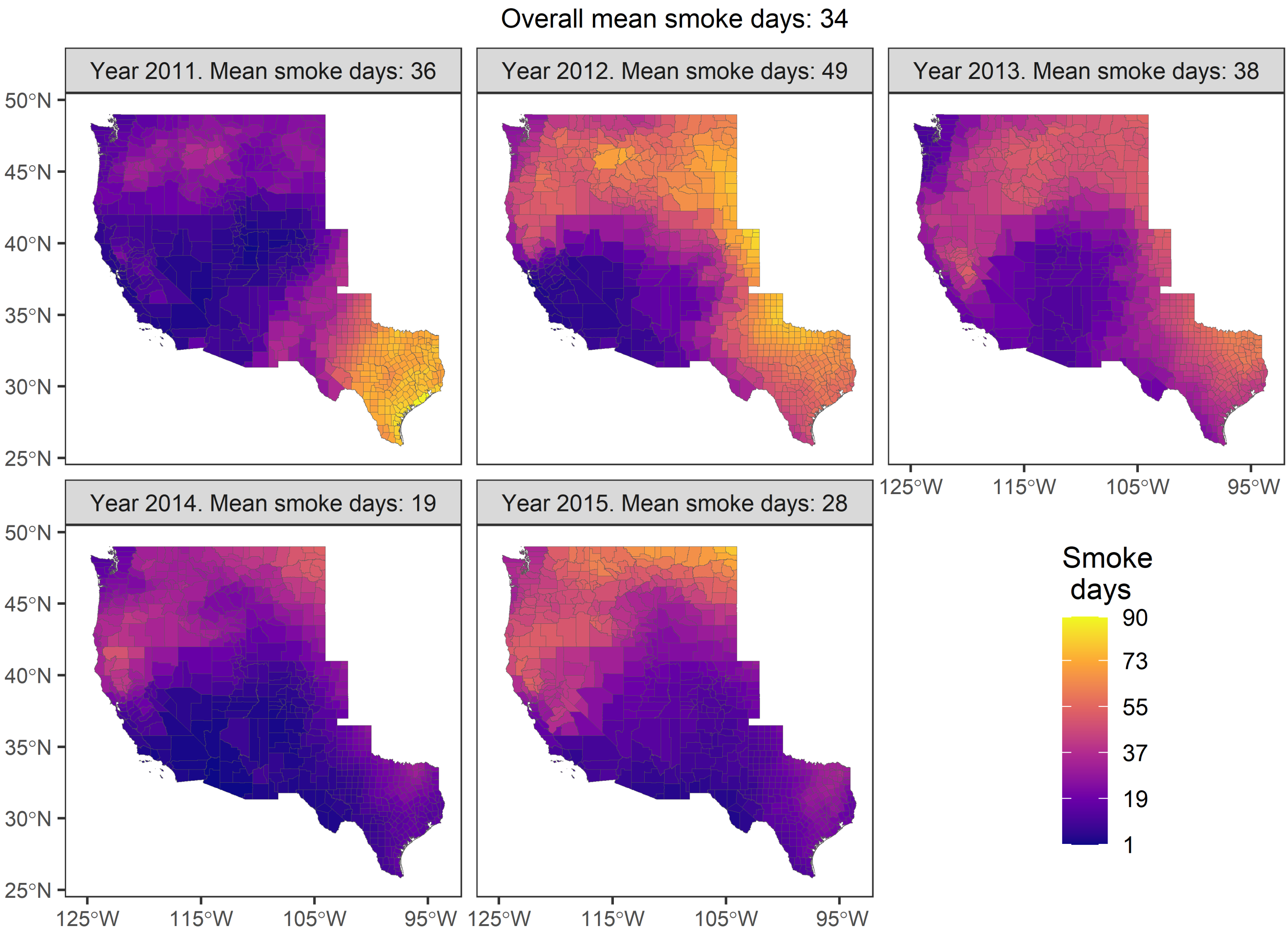
Figure 1: Annual Number of Smoke Days per County



Notes: This figure represents the annual average number of smoke days of any intensity by county across the Western United States over the period 2011-2015. Smoke counts are calculated based on the Hazard Mapping System smoke plumes data.

Table 1: Summary Statistics

	Observations	Mean	SD	Min	Max
Daily smoke: any	914481	0.1231	0.32	0.00	1.00
Daily smoke: low	914481	0.0939	0.27	0.00	1.00
Daily smoke: medium	914481	0.0225	0.13	0.00	1.00
Daily smoke: heavy	914481	0.0068	0.07	0.00	1.00
Daily temperature (°C)	914481	16.4232	9.02	-27.65	39.09
Number of crashes	914481	0.0385	0.22	0.00	8.00
Number of vehicles involved	914481	0.0594	0.38	0.00	20.00
Number of persons involved	914481	0.0912	0.66	0.00	93.00
Number of DUI involved	914481	0.0123	0.12	0.00	5.00

Notes: The observation unit is a county-by-day. All smoke-related variables calculated as the fraction of area a county being covered with smoke plumes on a day. All crash-related variables calculated as a number of relevant fatal crashes on a day. DUI = driving under the influence.

Table 2: Main Results

	(1) AQI and Smoke	(2) Main Model	(3) Daily Lag	(4) Weekly Lag
Panel A: Any smoke				
Smoke	12.2191***	0.0030***	0.0025***	0.0025***
	(0.5388)	(0.0009)	(0.0009)	(0.0010)
Smoke lag			0.0011	0.0003
			(0.0010)	(0.0002)
Panel B: Smoke intensities				
Smoke: low	8.1141***	0.0030***	0.0026***	0.0025**
	(0.3689)	(0.0010)	(0.0010)	(0.0010)
Smoke: medium	18.6617***	0.0025	0.0023	0.0021
	(0.8823)	(0.0016)	(0.0018)	(0.0018)
Smoke: heavy	38.0199***	0.0050*	0.0041	0.0045
	(2.7098)	(0.0028)	(0.0028)	(0.0029)
Smoke: low, lag			0.0015	0.0005
			(0.0011)	(0.0003)
Smoke: medium, lag			-0.0020	-0.0003
			(0.0020)	(0.0005)
Smoke: heavy, lag			0.0044	0.0005
			(0.0036)	(0.0008)
Observations	352,898	914,481	914,481	914,481
Mean of outcome	44.1002	0.0424	0.0424	0.0424
FE: County	X	X	X	X
FE: Date	X	X	X	X

Notes: The dependent variable is AQI index in column 1 and a number of crashes on the reference day in other columns. The main independent variable is a fraction of county being covered with any smoke (Panel A) or respective wildfire smoke intensity (Panel B) on a day. All columns contain weather controls and include county together with day fixed effects. Column 3 and 4 additionally control for a number of crashes on the previous day and week, respectively. Standard errors are clustered at the county level. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Other Variables

	(1) Fatal Crashes	(2) Vehicles Involved	(3) Persons Involved	(4) Drunk Drivers
Panel A: Any smoke				
Smoke	0.0026***	0.0045***	0.0055**	0.0011**
	(0.0008)	(0.0014)	(0.0023)	(0.0005)
Panel B: Smoke intensities				
Smoke: low	0.0025***	0.0047***	0.0057**	0.0009*
	(0.0008)	(0.0015)	(0.0025)	(0.0005)
Smoke: medium	0.0025*	0.0030	0.0039	0.0013
	(0.0014)	(0.0023)	(0.0043)	(0.0010)
Smoke: heavy	0.0052**	0.0060	0.0086	0.0028*
	(0.0025)	(0.0041)	(0.0070)	(0.0015)
Observations	914,481	914,481	914,481	914,481
Mean of outcome	0.0385	0.0594	0.0912	0.0123

Notes: Column name indicates the independent variable used. The main independent variable is a fraction of county being covered with any smoke (Panel A) or respective wildfire smoke intensity (Panel B) on a day. All columns contain weather controls and include county together with day fixed effects. Standard errors are clustered at the county level. Significance codes: * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 4: Heterogeneous Effects

	(1) Metropolitan Area	(2) Non-Metro: Urban Area	(3) Non-Metro: Rural Area	(4) Weekdays	(5) Weekends
Panel A: Any smoke					
Smoke	0.0086***	0.0003	0.0008	0.0025**	0.0041**
	(0.0023)	(0.0009)	(0.0008)	(0.0010)	(0.0019)
Panel B: Smoke intensities					
Smoke: low	0.0088***	-0.0001	0.0003	0.0021**	0.0046**
	(0.0024)	(0.0011)	(0.0008)	(0.0010)	(0.0021)
Smoke: medium	0.0057	0.0011	0.0032*	0.0042**	-0.0013
	(0.0043)	(0.0020)	(0.0019)	(0.0021)	(0.0035)
Smoke: heavy	0.0144*	0.0021	-0.0007	0.0025	0.0124**
	(0.0083)	(0.0032)	(0.0029)	(0.0033)	(0.0056)
Observations	298,439	423,014	193,028	652,630	261,851
Mean of outcome	0.0990	0.0189	0.0062	0.0377	0.0540

Notes: Column name indicates the subset of data used. The dependent variable used is a number of crashes on the reference day. The main independent variable is a fraction of county being covered with any smoke (Panel A) or respective wildfire smoke intensity (Panel B) on a day. All columns contain weather controls and include county together with day fixed effects. Standard errors are clustered at the county level. Significance codes: * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 5: Robustness Checks

	(1) Main Model	(2) Fatality Rate (per 6M cars)	(3) Population Weights	(4) Poisson Regression	(5) Future Smoke
Panel A: Any smoke					
Smoke	0.0030***	0.0028**	0.0204*	0.0840***	0.0026***
	(0.0009)	(0.0014)	(0.0109)	(0.0220)	(0.0009)
Smoke: next day					0.0010
					(0.0010)
Panel B: Smoke intensities					
Smoke: low	0.0030***	0.0029*	0.0183**	0.0742***	0.0026***
	(0.0010)	(0.0015)	(0.0086)	(0.0243)	(0.0010)
Smoke: medium	0.0025	0.0005	0.0229	0.0953*	0.0015
	(0.0016)	(0.0029)	(0.0218)	(0.0493)	(0.0018)
Smoke: heavy	0.0050*	0.0096*	0.0475	0.2028**	0.0037
	(0.0028)	(0.0056)	(0.0390)	(0.0890)	(0.0031)
Smoke: low, next day					0.0007
					(0.0011)
Smoke: medium, next day					0.0027
					(0.0019)
Smoke: heavy, next day					0.0014
					(0.0033)
Observations	914,481	914,481	914,481	914,481	914,481
Mean of outcome	0.0424	0.0406	0.4121	0.0424	0.0424

Notes: The dependent variable used in all models but column 2 is a number of crashes on the reference day. The dependent variable used in column 2 is a fatality crash rate per 6 million of vehicles registered in the state. The main independent variable is a fraction of county being covered with any smoke (Panel A) or respective wildfire smoke intensity (Panel B) on a day. All columns contain weather controls and include county together with day fixed effects. Column 3 includes county population weights. Column 4 is estimated using Poisson regression. Column 5 includes a fraction of area affected by corresponding smoke on the next day. Standard errors are clustered at the county level. Significance codes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.