Orange Skies:
An Assessment of Wildfire Smoke Exposure in the United States

by

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Abstract

Air quality in the United States has improved substantially over the last few decades. However, there are concerns that climate change may undermine this progress through an increase in the incidence and severity of wildfires. Using satellite-derived data, I examine census tract-level wildfire smoke exposure in the contiguous United States and its relationship to air pollution. First, I document that average annual wildfire smoke exposure days increased substantially in the U.S. between 2006 and 2020. Second, I show that rural communities, lower-income census tracts, and areas with higher proportions of children are disproportionately exposed to more wildfire smoke overall. However, smoke exposure-demographic patterns are changing. Urban census tracts, poorer census tracts, and communities with higher proportions of Hispanic Americans are positively correlated with growth in smoke exposure over time. Third, I estimate the relationship between smoke exposure days and average annual air pollution levels. I find that annual $PM_{2.5}$ concentrations in the U.S. between 2006 and 2016 would have been 7% lower on average in the absence of wildfire smoke. Back-of-the-envelope calculations suggest that wildfire smoke exposure reduces aggregate life expectancy in the United States by 13.128 million life-years each year.

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1 Introduction

Air pollution from wildfires is increasing, which threatens to undermine the progress the U.S. has made over the past few decades in improving air quality (Burke et al., 2021; McClure and Jaffe, 2018; Colmer et al., 2020). Recent and dramatic events in California and much of the western U.S. have raised awareness of the "Smoke Days" phenomenon. These are days in which smoke from wildfires diffuses into the atmosphere, reducing air quality, and in some instances, turning the sky orange.

Wildfire smoke presents a significant threat to human health and quality of life. Several studies link wildfire smoke exposure to adverse health outcomes, such as increased respiratory and cardiovascular mortality and morbidity (Adetona et al., 2016; Reid et al., 2016; Xu et al., 2020). Some evidence suggests that air pollution from wildfire smoke is more harmful to human health than air pollution from other sources (Aguilera et al., 2021; Wegesser et al., 2009), but this topic is relatively understudied (Kochi et al., 2010). Economists have quantified the costs of smoke-induced mortality (Burke et al., 2021; Miller et al., 2017), smoke-induced morbidity (Dittrich and McCallum, 2020; Kochi et al., 2010; Miller et al., 2017), losses in labor earnings (Borgschulte et al., 2019), and reductions in self-reported life satisfaction (Jones, 2017, 2018; Richardson et al., 2012). By all estimates, the costs associated with wildfire smoke far exceed the costs associated with the wildfires themselves. This is because smoke, and the air pollutants within, can travel far distances from the location of the fires due to wind, thereby affecting a much wider population than which the fire directly affects (Reisen et al., 2015).

Wildfires are becoming increasingly prevalent in the United States. Total acres burned in the U.S. between 2003 and 2020 is nearly double the area burned between 1985 and 2002, and annual fire suppression costs now exceed $2 billion (NIFC, 2020). The environmental science literature documents this phenomenon thoroughly and provides a few important explanations for the rise in American wildfire activity since the 1980's. These reasons include climate (Bowman et al., 2020; Westerling et al., 2006; Westerling, 2016) and anthropogenic climate change (Abatzoglou and Williams, 2016; Goss et al., 2020; Williams et al., 2019), the expansion of the Wildland-Urban Interface (Burke et al., 2021; Radeloff et al., 2018; Syphard et al., 2007), and a history of fire suppression beginning in the late 19th century (Marlon et al., 2012; Miller et al., 2009; Parks et al., 2015; Steel et al., 2015). Of all these reasons, climate is the most significant (Abatzoglou and Williams, 2016; Williams et al., 2019). The hotter and drier conditions associated with human-caused climate change have made wildfires more frequent, more severe, and have extended the wildfire season.

This paper explores how exposure to wildfire smoke is distributed across the United

States and estimates the relationship between wildfire smoke and fine particulate matter air pollution ($PM_{2.5}$). I do this using high resolution, remotely-sensed satellite smoke plume and annual $PM_{2.5}$ data.

First, I examine how smoke exposure is distributed across space and how it has evolved over time. I find that the average census tract experiences 27 smoke days a year, or 110 annual smoke hours. I look at overall wildfire smoke exposure, but I also distinguish between mild and intense smoke exposure. The northern and western regions of the country get the most smoke and the most intense smoke. Furthermore, I find that wildfire smoke exposure is a growing issue. Between 2006 and 2020, average exposure to wildfire smoke more than doubled, with most regions exhibiting a similar pattern.

Second, I explore how wildfire smoke exposure is distributed across socioeconomic and demographic groups. I find that rural census tracts, lower income census tracts, and census tracts with higher proportions of children endure a disproportionate amount of annual smoke exposure. Unlike traditional sources of air pollution, wildfire smoke does not appear to disproportionately affect Black or Hispanic communities. However, this pattern is changing. Urban census tracts, higher poverty census tracts, and census tracts with higher proportions of Hispanic Americans are associated with the highest growth in smoke exposure over time.

Third, I evaluate the relationship between wildfire smoke and average annual $PM_{2.5}$ exposure. I estimate that, on average, an additional day of smoke is associated with a 0.017 $\mu g/m^3$ increase in annual average $PM_{2.5}$ concentrations. Back-of-the-envelope calculations suggest that this pollution burden associated with average wildfire smoke exposure reduces life expectancy by 0.04 life-years per American each year, 13.128 million life-years in total. Intense smoke exposure episodes are associated with more substantial reductions in air quality. Taken at face value, my estimates indicate that annual average $PM_{2.5}$ concentrations would have, on average, been 7% lower in the absence of wildfire smoke.

I contribute to the existing literature in several ways. First, I build upon a previously-used method for identifying smoke exposure that relies on remotely-sensed, satellite smoke plume data. Other studies have used satellite smoke plume data for identifying smoke exposure (Borgschulte et al., 2019; Burke et al., 2021; Miller et al., 2017), but most only define smoke exposure as binary. However, not all smoke exposure is equal. My approach distinguishes annual smoke exposure days of varying intensity. Other work has used chemical transport models (CTM's) to simulate wildfire smoke dispersion (Jiang and Enki Yoo, 2019; O'Dell et al., 2019). While CTM's provide important information about smoke exposure that satellite smoke data does not, they require advanced consideration for fuel consumption parameters, emissions estimates, and atmospheric chemistry. Wildfire smoke analyses that use CTM's tend to be limited to regional and seasonal analyses. I evaluate wildfire smoke exposure across the entire contiguous U.S. between 2006 and 2020. As such, this paper provides a more systematic analysis of wildfire smoke exposure.

Second, I advance our understanding of who in society endures disproportionate exposure to wildfire smoke. This builds on and refines a literature documenting other forms of air pollution disparities (Colmer et al., 2020). In general, nationwide analyses of smoke exposure and demographics have thus far been limited (Burke et al., 2021).

Third, this paper provides the first systematic analysis of wildfire smoke's relationship to average annual air pollution exposure in the United States. I use $PM_{2.5}$ concentrations that are derived from satellite data and chemical transport models. The satellite data provides annual $PM_{2.5}$ measurements on a $0.01° \times 0.01°$ grid for ~ 8.6 million distinct locations - enough spatial resolution to provide $PM_{2.5}$ data for all census tracts in the contiguous United States. Previous scholarship has used ground monitor data when estimating the relationship between wildfire smoke and $PM_{2.5}$ levels (Borgschulte et al., 2019; Brey et al., 2018; Burke et al., 2021; McClure and Jaffe, 2018; Miller et al., 2017). Monitor data provides an accurate depiction of ground-level $PM_{2.5}$ concentrations, but only for a small number of locations. Only 6% of counties in the U.S. have frequently active air pollution ground monitors, mostly in urban areas, covering less than half the national population (Colmer et al., 2020).[1]

This paper proceeds as follows. Section 2 outlines the data. Section 3 describes smoke exposure in the U.S., spatially, temporally, and demographically. Section 4 examines the relationship between smoke and air pollution. Section 5 concludes.

2 Data

2.1 Wildfire Smoke Data

Data on wildfire smoke comes from the National Oceanic and Atmospheric Administration's (NOAA) Hazard Mapping System (HMS)[2].

The HMS contains daily wildfire smoke plume data going back to August 2005. Seven NOAA and NASA satellites orbiting at different angles and times of day produce 1 km resolution images of smoke plumes above the contiguous United States. Trained HMS satellite analysts then finalize the smoke shapefiles by hand drawing the contours and apparent density of each smoke polygon (Rolph et al., 2009; NOAA, 2021). The final product is a

[1]As a robustness check, I incorporate ground monitor $PM_{2.5}$ data into the analysis and get comparable results. This mitigates the potential concern that satellite-derived smoke and pollution data may be mechanically associated, rather than representing the relationship between wildfire smoke and $PM_{2.5}$ concentrations on the surface.

[2]https://www.ospo.noaa.gov/Products/land/hms.html#data

geocoded smoke shapefile with the approximate start and end times of each smoke plume on that day. The HMS also started to report plume density starting in 2007, with qualitative denotations of *Thin*, *Medium*, and *Thick* smoke. The approximate smoke concentrations in micrograms per cubic meter are 0-10 $\mu g/m^3$, 10-21 $\mu g/m^3$, and 21-32 $\mu g/m^3$ for each category.

NOAA's HMS is one of the best sources of wildfire smoke data in the United States with its large spatial extent and easy access. For these reasons, several of the past papers on wildfire smoke exposure have used HMS smoke data (Borgschulte et al., 2019; Burke et al., 2021; Miller et al., 2017), instead of using more complex and demanding chemical transport models (CTM's) to simulate the dispersion of wildfire smoke (Jiang and Enki Yoo, 2019; O'Dell et al., 2019).

Despite its vast geographic extent and relative ease-of-use, there are a few shortcomings associated with HMS smoke data. Most importantly, HMS data does not distinguish smoke plumes from wildfires, prescribed burns, or agricultural fires (Rolph et al., 2009; NOAA, 2021). Given that smoke plumes can cover massive amounts of area, travel far from their source fires, and mix with other smoke plumes, linking individual smoke plumes to source fires is nearly impossible. The fact that satellite analysts cannot distinguish smoke by source may lead some to believe that HMS data overestimates smoke attributable to wildfires. However, HMS data more likely underestimates wildfire smoke due to challenges associated with identifying smoke plumes under nighttime, cloudy, or snowy conditions (Rolph et al., 2009; NOAA, 2021). Furthermore, the majority of acres burned in the U.S. comes from wildfires, and acres burned from prescribed and agricultural fires are relatively low and annually consistent (Burke et al., 2021; NIFC, 2020) [3]. Therefore, HMS data still provides the best available data on wildfire smoke exposure even though the raw data is not able to link smoke plumes to specific wildfires or other specific sources.

Additional limitations to satellite smoke data are important to mention. Satellite-based images cannot distinguish smoke plume height, and they can only imprecisely differentiate plume density (Burke et al., 2021). Denser plumes and those that are lower in the atmospheric column present the greatest threats to air quality. There is also growing evidence that smoke age is an important characteristic when considering the effect on air pollution and the associated health outcomes (Brey et al., 2018; O'Dell et al., 2020). HMS data does not distinguish the age of smoke plumes.

The above caveats notwithstanding, I use the HMS satellite smoke plume data to calculate annual smoke exposure for every census tract in the contiguous United States ($\sim 65,000$)

[3]Prescribed burned acres have increased only the the Southeast U.S.. This region is exposed to less smoke exposure than other regions.

between 2006 and 2020. The approximate sample size is 970,000 census tract-years (Table 1). I identify overall smoke exposure primarily with the use of "smoke days". This variable represents the total number of days in which there is any overhead smoke above a given census tract during a given year. I also look at a more granular measurement of annual smoke exposure with the use "smoke hours" (the difference between the end and start times of each visible smoke plume).

Lastly, I allow for differences in intensity of wildfire smoke exposure. I do this by identifying annual "thin smoke days", "medium smoke days", and "thick smoke days" according to the HMS's classifications of *Thin*, *Medium*, and *Thick* smoke. Priority goes to the thicker density in the case that there are two overhead smoke plumes with different densities on the same day. Thus, if there is a thin plume and a thick plume above the same census tract on the same day, I classify that day as a "thick smoke day". I incorporate density into the smoke hours variables as well.

2.2 $PM_{2.5}$ Data

Data on $PM_{2.5}$ concentrations comes from both satellite and ground monitor sources. The satellite-based $PM_{2.5}$ data comes from Meng et al. (2019). They derive annual average $PM_{2.5}$ concentrations across North America on a 0.01° X 0.01° grid, using Aerosol Optical Depth (AOD) from NASA satellites, as well as from the GEOS-Chem chemical transport model. Colmer et al. (2020) map this pollution data to same U.S. census tracts that I use in this paper. The original data includes annual average $PM_{2.5}$ concentrations for each census tract between 1981 and 2016. I restrict the data to include observations between 2006 and 2016, for a total sample size of over 714,000 census tract-years (Table 1). The large geographic extent of the satellite data allows for a nationwide analysis of the widespread pollution effects of wildfire smoke.

The primary source of $PM_{2.5}$ data and the smoke data come from satellite products. This raises concerns about the degree to which the relationship between these two products will provide information about ground-level $PM_{2.5}$ concentrations. The potential concern arises because both the smoke and pollution data are derived from Aerosol Optical Depth (AOD). Regressing two AOD-based sources of data runs the risk of mechanical correlations that do not reflect particulate pollution at surface levels. To explore this, I incorporate ground monitor pollution data into the analysis and compare results with the satellite data. The ground monitor data comes from the Environmental Protection Agency's Air Quality System (AQS) and contains 24-hour $PM_{2.5}$ concentrations for all monitors throughout the United States between 1997 and 2016. I apply several sample restrictions. I restrict the data to include monitors only from the contiguous U.S. and monitors that have data in every year between 2006 and 2016. I also require that each monitor has at least fifty 24-hour observations in each year, which is a reasonably sufficient sample size to derive an annual average. Finally, I account for seasonality. I require that for each monitor-year, there are a sufficient number of observations in each of the four seasons (each season contains at least 10% of all observations associated with that monitor-year). Once all restrictions are applied, the sample includes data from 307 ground monitors in forty different states, for a sample size of 3,300 census tract-years (Table 1).

2.3 Weather Data

I incorporate weather data to address the fact that both wildfire smoke exposure and overall $PM_{2.5}$ levels are correlated with weather. The weather data, updated from Schlenker and Roberts (2009), comes from the PRISM Climate Group. This data provides daily minimum and maximum temperature (in degrees Celsius) as well as total precipitation (in millimeters) on a 2.5 x 2.5 mile grid for the contiguous United States between 1950 and 2020. To ensure that as many census tracts as possible are assigned a value, I rasterize the spatial grid. I then derive daily-mean temperature by taking the arithmetic mean of daily minimum and maximum temperatures. Finally, I construct annual measures of average daily-mean temperature and total precipitation at the census tract-level between 2006 and 2016, for a total of approximately 710,000 census tract-years.

2.4 Demographic Data

Demographic data comes from the 2010 Decennial Census and the American Community Survey. The Decennial Census data provides information on population, race, ethnicity, and age-related variables. The American Community Survey includes economic characteristics such as income per capita and the poverty rate. Colmer et al. (2020) map the demographic data to the same census tracts that I use in this paper.

3 The Distribution of Wildfire Smoke Exposure in the United States

3.1 Smoke Exposure Across Space and Time

Table 1 shows that the average census tract in the United States experiences 27 smoke days a year. Most of such wildfire smoke exposure is mild, with the the majority of smoke days being of category *Thin*. Exposure to intense wildfire smoke (medium and thick smoke days), averages around five days a year.

Table 2 displays average smoke exposure days for the nine climate regions of the contiguous United States [4]. The Northern Rockies and Plains and the Upper Midwest endure the most exposure to wildfire smoke, overall and intense. Furthermore, the Northwest, West, and Ohio Valley regions experience a relatively high amount of intense smoke exposure. Figure 1 offers an extensive visualization of the spatial distribution of annual smoke days throughout the contiguous U.S.

I also examine how exposure to wildfire smoke has changed over the past fifteen years. As with wildfires themselves, smoke has progressively become more of an issue in the United States. Between 2006 and 2020, average annual smoke days across the country more than doubled, increasing by an average rate of 1.33 additional smoke days per year (Figure 2a). This trend in more frequent smoke exposure is evident in most regions throughout the country. As Figure S3 shows, all regions except for the Southeast exhibit noticeable increases in average annual smoke exposure over the sample period. In Figure S1, we are able to see that much of the country is "smokier" in the second half of the sample period versus the first half.

There is evidence that smoke exposure from wildfires is becoming more intense in addition to more frequent. Figure 2b shows that the proportion of smoke exposure days that involve thick smoke has increased over time. Thus, the average smoke day itself has become more severe.

3.2 Smoke Exposure and Demographics

To estimate the correlation between smoke exposure and demographics, I estimate the following bivariate regression model:

$$Smoke_c = \beta_1 Demographic_c + \epsilon_c$$

In one estimation, the dependent variable, $Smoke_c$ represents the mean number of smoke days in census tract c from 2006 through 2020. This gauges overall smoke exposure. In another estimation, $Smoke_c$ is the log change in smoke days between 2006 and 2020 for census tract c. This represents the growth rate in smoke exposure.

The independent variable, $Demographic_c$, represents a demographic for census tract c, recorded in the 2010 Census. These variables include population, race/ethnicity characteris-

[4] For more information, see:
https://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-regions.php

tics, age-related variables, income per capita, the poverty rate, and urban versus rural census tracts.

Figure 3a shows that, on average, smoke exposure is positively associated with rural census tracts, census tracts with higher proportions of children ($<$ 18 years of age), census tracts that have a larger White population, and census tracts that are lower income. This differs from patterns between demographics and more traditional sources of $PM_{2.5}$, to which Black, Hispanic, and urban communities typically get the most exposure (Colmer et al., 2020).

However, Figure 3b shows noticeably different correlations with the *growth rate* in smoke exposure. On average, smoke exposure is increasing more quickly in urban census tracts, higher poverty census tracts, and census tracts with a larger Hispanic population. One possible explanation for this is that the West and Southwest regions of the U.S. saw substantial increases in smoke exposure between 2006 and 2020 (Figure S3).

4 The Relationship between Wildfire Smoke and $PM_{2.5}$ Concentrations

Using census tract by year data, this section examines the average relationship between annual $PM_{2.5}$ concentrations and annual wildfire smoke exposure. I incorporate census tract-level $PM_{2.5}$, smoke, and weather data between the years 2006 and 2016.

4.1 Empirical Specification

This paper uses regression analysis to quantify the average relationship between annual smoke exposure and annual average $PM_{2.5}$. Given that measured air pollution levels may display geographic patterns, I specify a model that analyzes variation over time within the same census tracts. The model, in general terms, is as follows:

$$PM2.5_{cst} = \beta_1 Smoke_{cst} + Weather_{cst} + \alpha_c + \delta_{st} + \epsilon_{cst}$$

The outcome variable, $PM2.5_{cst}$, represents the annual average concentration of $PM_{2.5}$, in micrograms per cubic meter, for census tract c, in state s, in year t. In some estimations, I use only the satellite-based $PM_{2.5}$ data. In other regressions, I compare results between the satellite and ground monitor data. This analysis of wildfire smoke's relationship to air pollution using data from both satellite and ground monitor sources is the first of its kind.

The treatment variable is $Smoke_{cst}$, which represents the annual smoke coverage above census tract c, in state s, in year t. The primary treatment variable for overall smoke exposure is smoke days, although smoke hours provides an alternative temporal measurement. I also specify models that distinguish smoke exposure by intensity. For this, I use the HMS's classification of *Thin*, *Medium*, and *Thick* smoke. Priority goes to the thicker density in the case of spatial and temporal overlap, so these categories are mutually exclusive. No study before has specified the treatment of wildfire smoke with varying temporal or intensity measurements.

The model includes several control variables. To account for the fact that both wildfire smoke and pollution concentrations may be correlated with the weather, I control for temperature and precipitation. Specifically, the variables associated with $Weather_{cst}$ are annual average daily-mean temperature (in degrees Celsius) and annual total precipitation (in mm).

The main threat to identification is omitted variable bias. Both smoke exposure and overall air pollution exhibit geographic patterns. To account for all time-invariant unobserved heterogeneity, I include census tract fixed effects, α_c. These control for all omitted variables that vary across census tracts but not across time. For example, rural census tracts tend to get the most smoke exposure but the least overall air pollution. The opposite is true for urban census tracts given their geographic location and the fact that cities contain more anthropogenic sources of particulate pollution. Failing to control for omitted variables associated with rural versus urban census tracts would likely result in downward bias in the coefficient of interest. Census tract fixed effects control for all other time-invariant omitted variables as well.

Smoke exposure and $PM_{2.5}$ concentrations may also be correlated with omitted variables across time. To address this concern, I include state-by-year fixed effects, δ_{st}. This controls for all time-varying confounding factors that affect all census tracts equally within the same state. Examples include forest management policy, state air pollution regulations, and general economic activity.

4.2 Results

Table 3 reports estimates of the relationship between annual smoke exposure and annual average $PM_{2.5}$ concentrations using the satellite data products. In column (1) I estimate that, on average, an additional day of smoke is associated with a 0.017 $\mu g/m^3$ increase in annual $PM_{2.5}$ concentrations. This is 1.3% of the annual (within) standard deviation. This estimate is similar to Borgschulte et al. (2019), who estimate the relationship between wildfire smoke and annual $PM_{2.5}$ concentrations using ground monitor data. Taking the results at face value, $PM_{2.5}$ concentrations would have been 7% lower in the absence of wildfire smoke.

Back-of-the-envelope calculations suggest that average annual smoke exposure is associated with a reduction in life expectancy by 0.04 life-years per person each year, which equates to 13.128 million American life-years lost per year (Ebenstein et al., 2017; AQLI, 2021).[5] This is far greater than the annual loss of life associated with fires themselves (USFA, 2021).

In column (2) I distinguish between intense smoke exposure and mild exposure. I estimate that thick and medium smoke days are associated with more substantial increases in air pollution levels than days with thin smoke. Most smoke exposure episodes are mild (Table 1). However, understanding the pollution effects of intense wildfire smoke exposure is increasingly important, as trends indicate that annual smoke exposure from wildfires is becoming more severe in addition to more frequent. (Figure 2b).

Columns (3) and (4) replicate the analysis in columns (1) and (2) for smoke hours. When evaluated at the mean, the smoke hour estimates are smaller. This suggests that the number of exposures matters more than the duration of exposures.

As discussed, the satellite data products are both derived in part from raw Aerosol Optical Depth data. Consequently, one may be concerned that the estimated relationship captures a mechanical correlation, rather than the relationship between wildfire smoke and $PM_{2.5}$ exposure on the ground. To address this concern, I re-estimate the relationship using using EPA ground monitor data. Table 4 shows that the findings between the satellite and ground monitor data are similar across all models.

5 Conclusion

This paper reiterates the importance of addressing wildfire smoke exposure while also offering new insight into its full effects. I provide detailed information on the geographic and demographic distribution of smoke exposure, which has thus far been limited. Using satellite-derived $PM_{2.5}$ data, I provide the first nationwide analysis of the far-reaching air pollution effects from wildfires. The pollution burden associated with wildfires is a serious problem, likely resulting in substantial reductions in aggregate life expectancy each year, per back-of-the-envelope calculations. I also estimate that in the absence of wildfire smoke, counterfactual $PM_{2.5}$ concentrations would have, on average, been 7% lower, suggesting that wildfires are a small, but non-trivial component of overall $PM_{2.5}$ exposure. This analysis also shows that exposure to wildfire smoke in the United States is growing - a likely consequence of climate change. If trends continue as climate scientists predict, wildfires will become a

[5]Multiplying by the national average of 27 annual smoke days equals a 0.449 $\mu g/m^3$ increase in average annual $PM_{2.5}$ exposure. Using the referenced study for the basis of my calculation, I equate the smoke-related increase in annual $PM_{2.5}$ to reductions in life expectancy.

major threat to American air quality on a national scale.

The problem of wildfire smoke exposure demands greater consideration given the disparities we currently see and how these patterns are changing. The fact that smoke disproportionately affects communities with large percentages of children and low-income people is concerning, as these are two vulnerable subpopulations to pollution damages. Trends in the growth of smoke exposure are also concerning. Evidence from this paper shows that smoke is affecting urban population centers at an increasing rate, which suggests the economic damages from wildfire smoke may be increasing rapidly as well. My findings indicate that the returns to investing in wildfire management may be greater than previously thought. If we fail to account for the economic damages and distributional considerations associated with wildfire smoke exposure in cost-benefit analysis, then we will substantially underestimate the returns to wildfire mitigation policies.

The results from this study raise a number of questions for future research. The use of atmospheric or chemical transport models to simulate smoke dispersion could help to fill important gaps associated with the satellite-based smoke plume data. Specifically, models that focus on smoke height and smoke age would offer important information about the air pollution effects of wildfire smoke. NOAA's HYSPLIT is one of several CTM's which offer promising new approaches to simulating wildfire smoke dispersion on a large spatial and temporal scale (Brey et al., 2018; Stein et al., 2016). In addition, further research on improving estimates of total wildfire-specific air pollution would be beneficial. Region-specific and year-specific estimates of wildfire $PM_{2.5}$ would be particularly interesting. Having accurate measurements for total wildfire $PM_{2.5}$ is also important when measuring costs via dose-response functions, but even this method of assessing economic damages requires additional consideration. The growing evidence that wildfire $PM_{2.5}$ is more harmful to human health than $PM_{2.5}$ from other sources suggests that dose-response functions specifically for wildfire $PM_{2.5}$ might be necessary.

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Tables

Table 1: Summary Statistics

	(1) Mean	(2) Std. Dev.	(3) Observations
Air Pollution Variables			
Satellite ($\mu g/m^3$)	9.224	2.204	714,659
Ground Monitor ($\mu g/m^3$)	9.916	1.980	3,366
Smoke Variables			
Smoke Days	27.059	11.698	974,985
Thin Smoke Days	22.711	9.331	779,988
Medium Smoke Days	4.566	2.814	779,988
Thick Smoke Days	1.782	1.756	779,988
Smoke Hours	110.647	50.159	974,985
Thin Smoke Hours	93.921	39.471	779,988
Medium Smoke Hours	16.989	11.207	779,988
Thick Smoke Hours	6.173	6.500	779,988

Notes: The pollution variables are averaged across all census tracts for the years 2006-2016. The smoke variables are averaged across all census tracts for the years 2006-2020. Density-specific smoke variables are averaged across all census tracts for the years 2008-2020, not including 2009 since density is not reported at all in that year. I include between-census-tract standard deviations.

Table 2: Average Smoke Days by Climate Region

	(1) Smoke Days	(2) Medium Smoke Days	(3) Thick Smoke Days
Climate Regions			
Northeast	18.787	3.226	0.812
	(1.506)	(0.567)	(0.295)
Northern Rockies/Plains	49.289	11.094	4.999
	(7.605)	(1.917)	(1.680)
Northwest	30.459	7.774	5.144
	(8.990)	(2.558)	(2.479)
Ohio Valley	33.222	5.280	1.762
	(9.481)	(2.135)	(0.771)
Southeast	18.075	1.713	0.340
	(6.052)	(0.803)	(0.310)
South	34.063	4.645	1.012
	(9.110)	(1.823)	(0.753)
Southwest	20.157	4.365	2.132
	(7.108)	(1.841)	(1.254)
Upper Midwest	43.555	8.731	3.312
	(8.374)	(2.577)	(0.811)
West	22.130	4.237	3.426
	(8.559)	(2.550)	(2.421)

Notes: Averages are calculated by taking the mean of the smoke variables for all census tracts within each region throughout all years between 2006-2020. Smoke Days represents overall smoke exposure, while Medium and Thick Smoke Days represent intense exposure. The values in parentheses are the between-census-tract standard deviations.

Table 3: Wildfire Smoke and $PM_{2.5}$ (Satellite Data Only)

	Annual Average $PM_{2.5}$			
	(1)	(2)	(3)	(4)
Smoke Days	0.0166***			
	(0.00554)			
Thin Smoke Days		0.00579***		
		(0.00172)		
Medium Smoke Days		0.0196***		
		(0.00584)		
Thick Smoke Days		0.0410***		
		(0.00759)		
Smoke Hours			0.00262**	
			(0.000992)	
Thin Smoke Hours				0.000543
				(0.000412)
Medium Smoke Hours				0.00436*
				(0.00258)
Thick Smoke Hours				0.00533***
				(0.00198)
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
State-Year Fixed Effects	Yes	Yes	Yes	Yes
Outcome Mean	9.228	8.773	9.228	8.773
Observations	710908	517024	710908	517024

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Values in parentheses are standard errors, clustered at the state level. Each column represents a separate regression. Density-specific models have less observations since plume density is not reported in the raw data until 2007 and not at all in 2009.

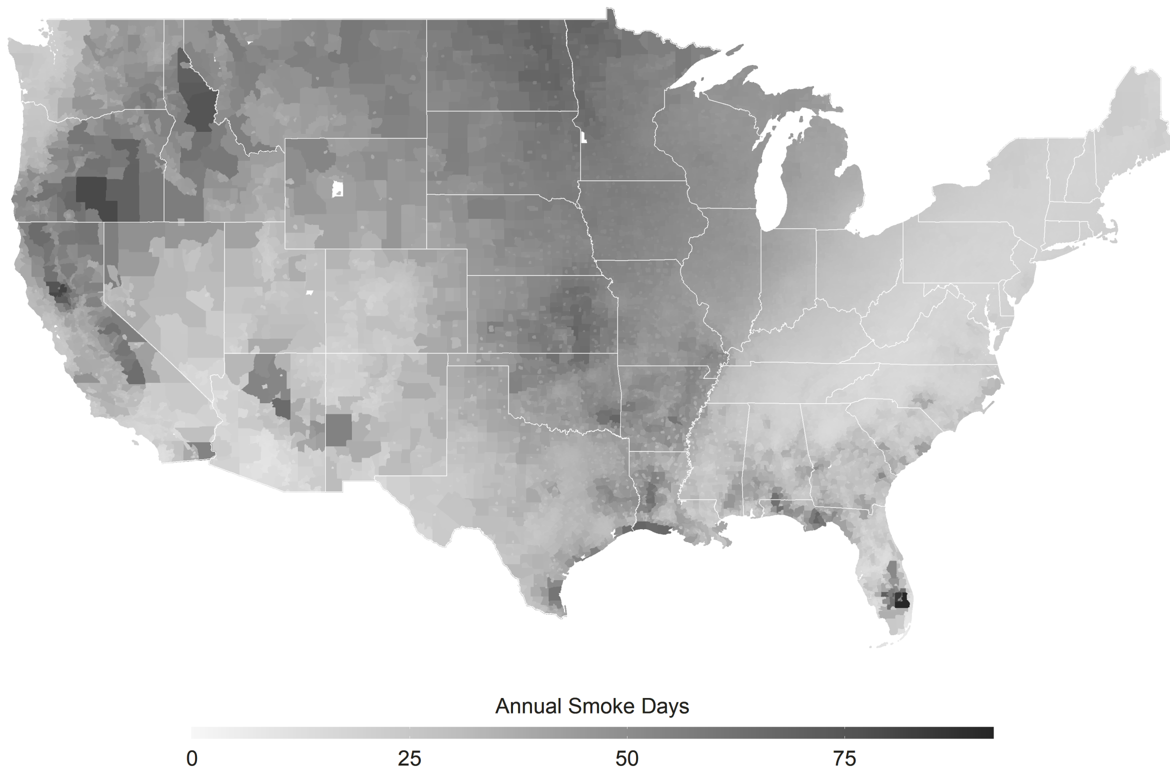
Table 4: Smoke Days and Annual Average $PM_{2.5}$ (Satellite vs. Monitor)

	(1) Satellite	(2) Ground Monitor	(3) Satellite	(4) Ground Monitor
Smoke Days	0.0134***	0.0181***		
	(0.00325)	(0.00450)		
Thin Smoke Days			-0.000646	0.0000879
			(0.00404)	(0.00576)
Medium Smoke Days			0.0187***	0.0286**
			(0.00537)	(0.0106)
Thick Smoke Days			0.0674***	0.0768***
			(0.0202)	(0.0206)
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
State-Year Fixed Effects	Yes	Yes	Yes	Yes
Outcome Mean	9.746	9.939	9.235	9.372
Observations	3322	3322	2416	2416

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the state level. Each column represents a separate regression. For each estimation, I restrict the satellite data to include only the observations that match with the ground monitor data.

Figures

Figure 1: Average Annual Smoke Days throughout the U.S. (2006-2020)

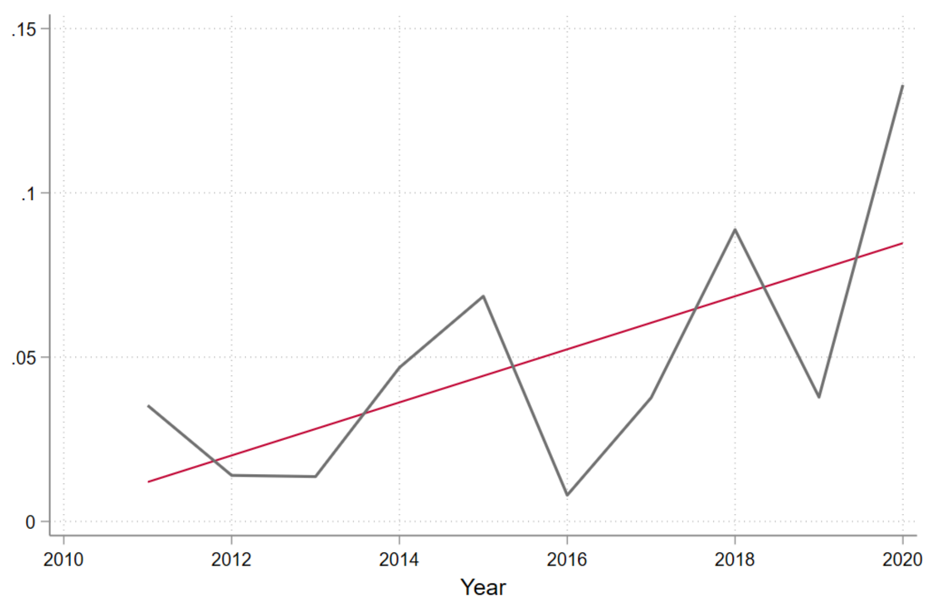


Notes: Smoke days are averaged in each census tract across all years 2006-2020.

Figure 2: National Trends in Wildfire Smoke Exposure

(a) Smoke Days

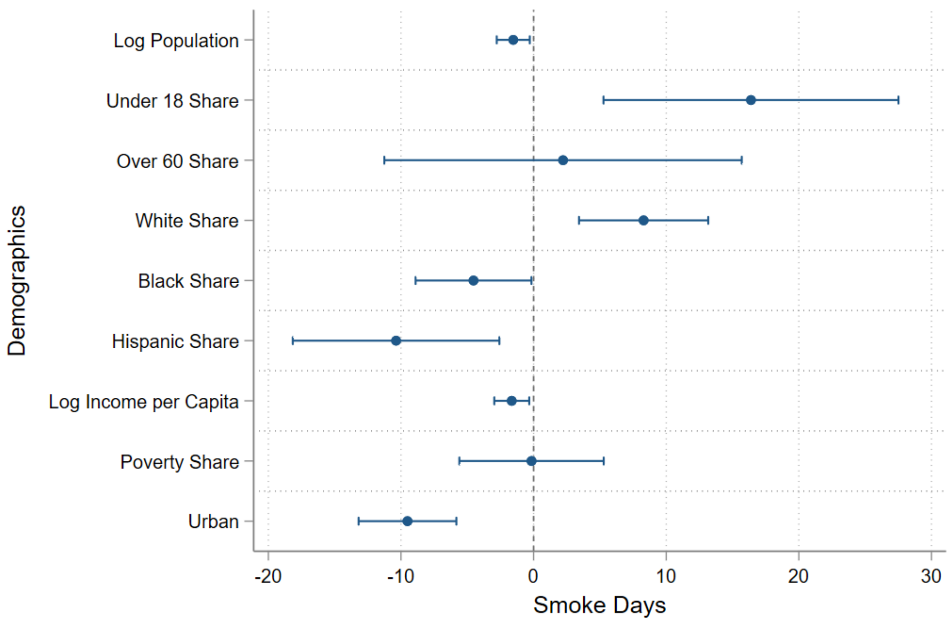
(b) Percent Thick Smoke Days



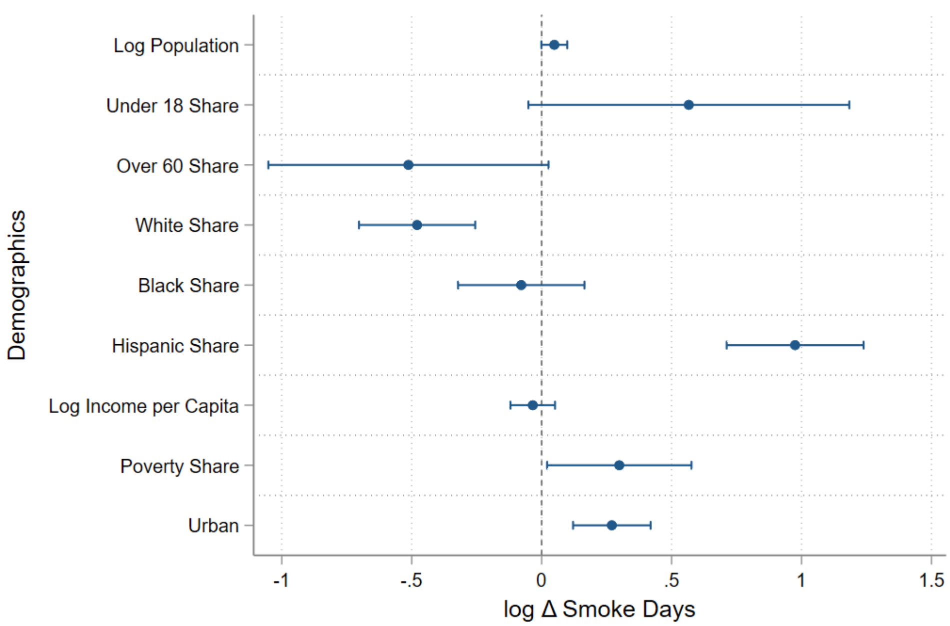
Notes: Smoke days are averaged across all census tracts in each year. The "Percent Thick Smoke Days" figure represents the percent of all smoke days with thick smoke.

Figure 3: Smoke Exposure and Demographics

(a) Overall Smoke Exposure



(b) Percent Change in Smoke Exposure



Notes: Coefficient plots display the results of bivariate regressions. The dependent variable of panel (a) is mean smoke days in each census tract between 2006 and 2020. Panel (b) looks at the percent change in smoke days for each census tract between 2006 and 2020.

Appendix

Table S1: Smoke Hours and Annual Average $PM_{2.5}$ (Satellite vs. Monitor)

	(1) Satellite	(2) Ground Monitor	(3) Satellite	(4) Ground Monitor
Smoke Hours	0.00302***	0.00367**		
	(0.00104)	(0.00144)		
Thin Smoke Hours			0.000839	0.00159**
			(0.000682)	(0.000756)
Medium Smoke Hours			0.00348	0.00559
			(0.00261)	(0.00421)
Thick Smoke Hours			0.0182***	0.0152***
			(0.00334)	(0.00430)
Census Tract Fixed Effects	Yes	Yes	Yes	Yes
State-Year Fixed Effects	Yes	Yes	Yes	Yes
Outcome Mean	9.746	9.939	9.235	9.372
Observations	3322	3322	2416	2416

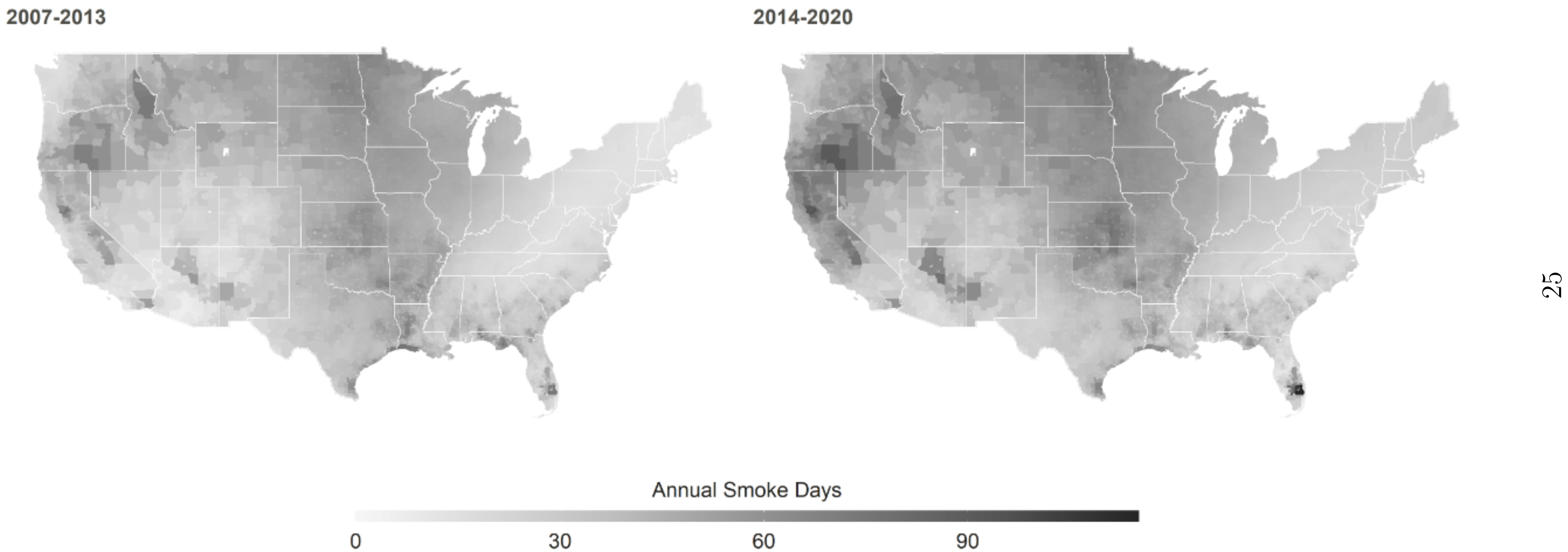
Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the state level. Each column represents a separate regression.

Table S2: Smoke Exposure and Demographics

	(1) Smoke Days	(2) log Δ Smoke Days	(3) N(Census Tracts)	(4) Outcome Means
Log Population	-1.533** (0.619)	0.0487* (0.0247)	64735, 64701	27.044, 1.256 (11.693), (0.487)
Under 18 share	16.39*** (5.531)	0.566* (0.307)	64735, 64701	27.044, 1.256 (11.693), (0.487)
Over 60 share	2.220 (6.701)	-0.513* (0.268)	64735, 64701	27.044, 1.256 (11.693), (0.487)
White Share	8.295*** (2.422)	-0.479*** (0.111)	64735, 64701	27.044, 1.256 (11.693), (0.487)
Black Share	-4.530** (2.172)	-0.0785 (0.121)	64735, 64701	27.044, 1.256 (11.693), (0.487)
Hispanic Share	-10.37** (3.874)	0.975*** (0.131)	64735, 64701	27.044, 1.256 (11.693), (0.487)
Log Income Per Capita	-1.646** (0.656)	-0.0342 (0.0426)	64682, 64648	27.047, 1.256 (11.694), (0.487)
Poverty Share	-0.156 (2.707)	0.299** (0.138)	64703, 64669	27.046, 1.256 (11.694), (0.487)
Urban	-9.508*** (1.833)	0.270*** (0.0742)	48151, 48122	26.527, 1.277 (11.705), (0.492)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Each row indicates separate bivariate regressions. The dependent variables are the smoke variables, averaged across each census tract between 2006 and 2020. Smoke Days are the total number of smoke exposure days. Log Δ Smoke Days represents the percent change in smoke days between 2006 and 2020. The independent variables are demographics from the 2010 census. Values in parentheses associated with each regression coefficient are standard errors, clustered at the state level. Outcome means are for the two respective smoke variables, and values in parentheses beneath are standard deviations.

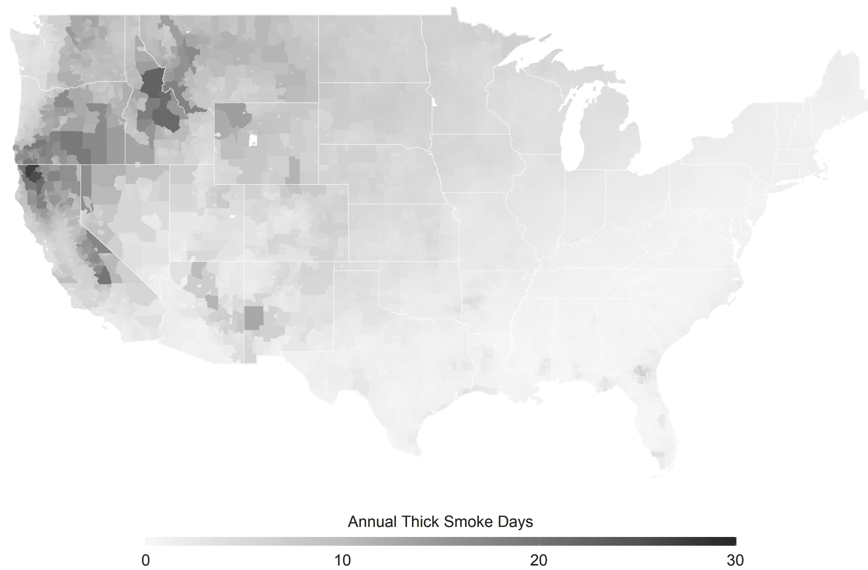
Figure S1: Average Annual Smoke Days 2007-2013 vs. 2014-2020



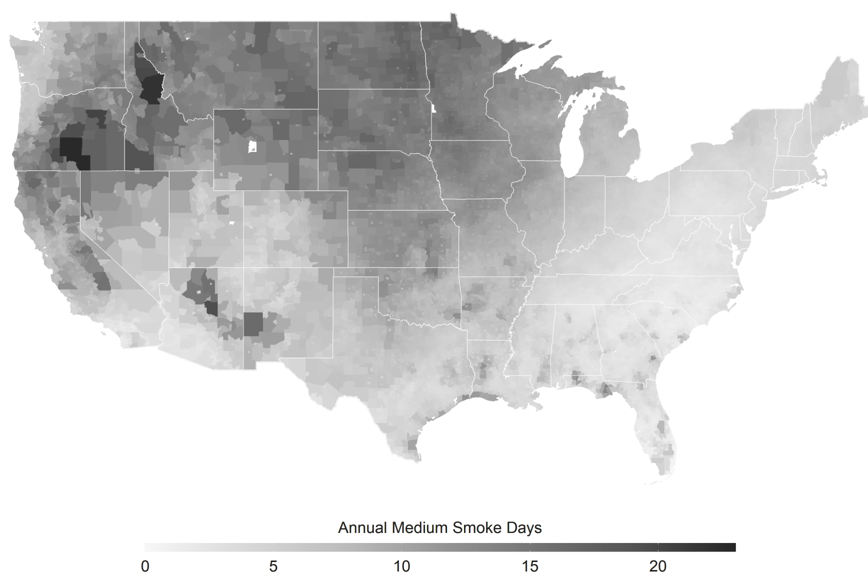
Notes: Smoke days are averaged in each census tract across all years of the two sample periods.

Figure S2: Intense Smoke Exposure Days throughout the U.S. (2006-2020)

(a) Average Annual Thick Smoke Days

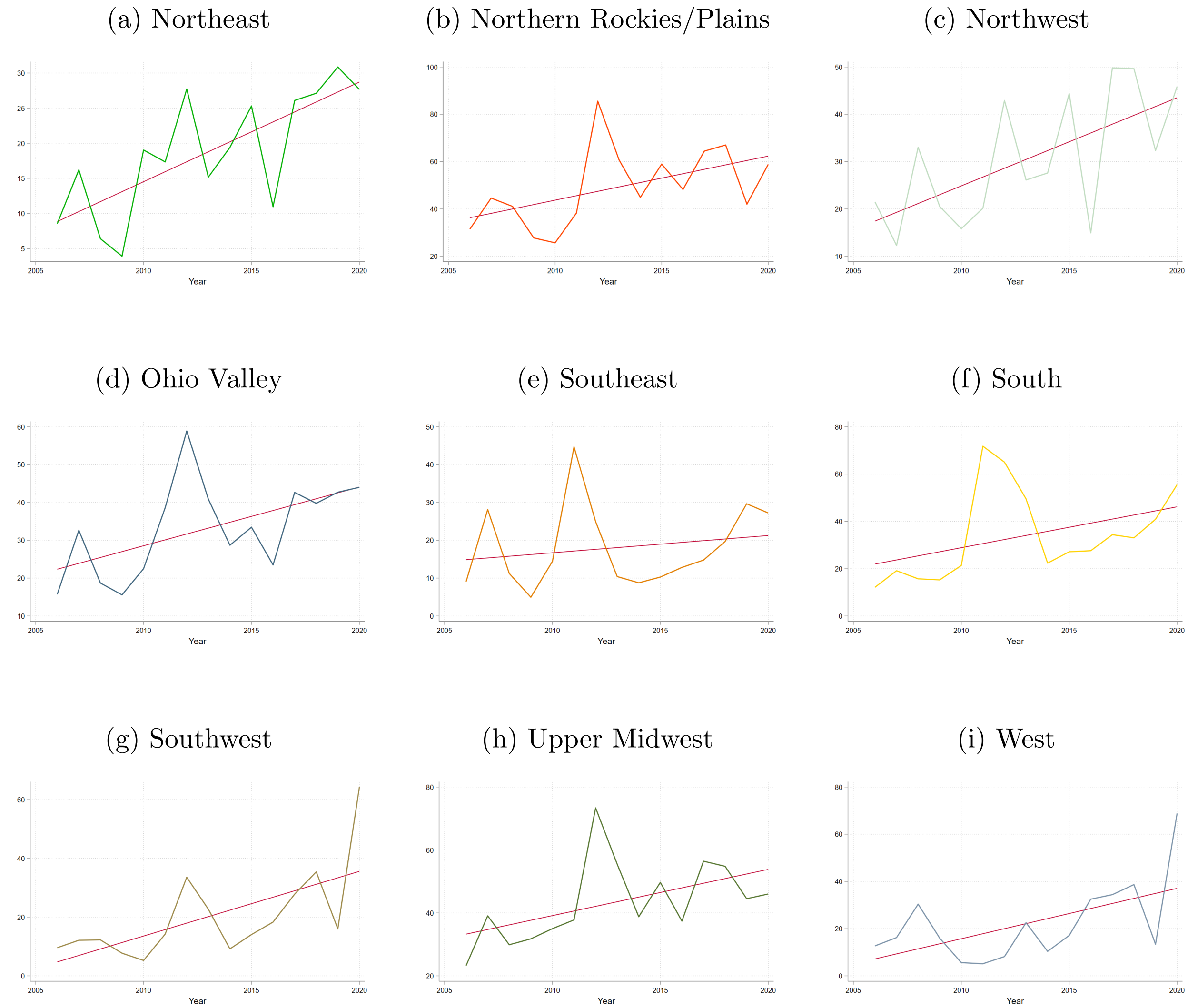


(b) Average Annual Medium Smoke Days



Notes: Maps display average annual Thick and Medium smoke days according to the HMS definition of *Thick* and *Medium* smoke. Averages are for each census tract between 2006 and 2020.

Figure S3: Average Annual Smoke Days by Region



Notes: Annual smoke days are averaged across all census tracts within the same region. For more information on the choice of climate regions, see `https://www.ncdc.noaa.gov/monitoring-references/maps/us-climate-regions.php`.