The Relationship Between Monthly Air Pollution and Violent Crime Across the United States

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Abstract

Recent evidence suggests a relationship between short-term pollution exposure and crime, with a particular emphasis on aggressive behavior. However, the previous analyses are limited in geographic scope. In this paper, we estimate the effect of fine particulate air pollution ($PM_{2.5}$) exposure on crime across 99% of counties in the contiguous United States. We combine monthly data on crime, $PM_{2.5}$, and satellite-derived smoke plumes for a ten-year period. We use adjusted satellite-based landscape fire smoke plume data as an instrument for overall changes in $PM_{2.5}$. Our findings are consistent with previous research and suggest that increases in $PM_{2.5}$ raise violent crime rates, and specifically assaults. Our results indicate the effect is relatively homogeneous across the U.S. However, we find the effect is positively correlated with county median age, suggesting older populations are more susceptible to changes in air pollution. Our results indicate a need for more research on the physiological and social mechanisms behind the measured effects.

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1 Introduction

Relationships between pollution exposure and adverse health outcomes have been established by many academic disciplines. Epidemiological and public health studies document a variety of negative health effects associated with exposure to airborne particulate matter (PM) (Archsmith et al., 2018; Currie et al., 2014; Deryugina et al., 2016; Di et al., 017a,b; Pope and Dockery, 1999; Pope III and Dockery, 2006; Schlenker and Walker, 2016; Seaton et al., 1995). Beyond the direct health effects, the economics literature has also established that air pollution exposure negatively effects cognitive function (e.g., Bishop et al., 2018; Graff Zivin and Neidell, 2012, 2013; Lavy et al., 2014) and labor productivity (e.g., Borgschulte et al., 2018; Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015), and imposes substantial welfare costs (Anderson, 1999; Bishop and Murphy, 2011).

Despite the considerable body of research on pollution and health outcomes, two recent manuscripts have identified an overlooked impact of pollution: the effect of short-term pollution exposure on aggression (Burkhardt et al., 2018; Herrnstadt et al., 2016). Aggressive behavior can impose psychological costs as well as police enforcement costs on society. However, both of the previous studies are limited in geographic scope and do not explore effect heterogeneity.[1] In this paper, we study the effect of air pollution on aggression in 99% of U.S. counties (2,977 total counties) over a ten year period. The geographic scope of our data allows us to test for heterogeneity in the treatment effect across sociodemographic and regional dimensions, providing important clues towards understanding the underlying physiological processes.

We find that a 1 μg/m^3 increase in the monthly average $PM_{2.5}$ increases violent crime rates by 0.53% per month per county, which translates into an additional 327 additional violent crimes per month on average across the contiguous U.S.[2] This primary effect is driven entirely by increases in assaults, which are indicative of impulsive and aggres-

[1] Herrnstadt et al. (2016) study this relationship in Chicago and Los Angeles while Burkhardt et al. (2018) study the relationship in 391 counties in the United States.

[2] $PM_{2.5}$ is defined as the mass concentration of particulate matter with aerodynamic diameters smaller than 2.5 μm.

sive behavior. However, we find no significant effect of $PM_{2.5}$ on other violent or non-violent crimes (e.g., murder, burglary). These results are consistent with previous estimates (Burkhardt et al., 2018; Herrnstadt et al., 2016); and, together, our results highlight an important social cost of pollution that is currently absent from policy discussions.

The causal mechanisms underlying the relationship between short-term pollution exposure and aggression are not well understood. Research in epidemiology indicates that pollution exposure can have short-term effects on cognitive skills, anxiety, and certain behaviors associated with criminal or violent activities (Kioumourtzoglou et al., 2017; Lu et al., 2018; Power et al., 2015). In light of this evidence, we hypothesize that the relationship between pollution and aggression is driven by physiological processes and is thus uniform across the U.S. and does not depend on observable sociodemographics such as income or race.

Our second finding indicates that the effect of $PM_{2.5}$ on violent crime is heterogeneous across one key dimension, a rejection of our primary hypothesis. Though the relationship between $PM_{2.5}$ and violent crime is present across the entire U.S., we find statistical differences in the relationship by median age. In particular, we find the effect is largest in counties with older populations. The treatment effects by age bracket are statistically different and range from 0.43%-1.3% more violent crimes per county per month for a 1 $\mu g/m^3$ increase in the monthly average $PM_{2.5}$. In contrast, we find the effect is largely homogeneous across regions of the U.S. and across other sociodemographic indicators (e.g., income, education, population), which also suggests that higher incomes do not moderate the effect.

We merge three datasets to identify the effect of $PM_{2.5}$ on crime. First, we use data on criminal activity from the Uniform Crime Reporting Program (UCR) managed by the Federal Bureau of Investigation (UCR, 2004). The dataset contains monthly level crime counts for a handful of categories of crime spanning nearly all of the U.S. population between 2006-2015. Second, we merge the crime data with gridded daily pollution ($PM_{2.5}$) estimates (15 km resolution) spanning the contiguous U.S. from 2006-2015 (Burkhardt et al., 2018; Lassman et al., 2017). Our interpolated data provides gridded estimates (15 km grid) of $PM_{2.5}$ over the entire United States for every day of the 2006-2015 period (Lassman et al., 2017).[3] Our third dataset includes data on landscape fire smoke plumes obtained from satellite imagery. The data is produced by the National Oceanic and Atmospheric Administration (NOAA) Hazard Mapping System (HMS, 2018). Smoke plumes generated by wild and prescribed fire as well as agricultural burning can travel hundreds or thousands of miles. We use these smoke plumes as a source of exogenous variation for observed $PM_{2.5}$.[4] We also include monthly average weather data and county-by-year fixed effects and month fixed effects to control for time-varying county specific unobservables and seasonal variation in crime and pollution.[5]

Our results have important implications for air pollution policy and future research. For instance, fire-smoke induced $PM_{2.5}$ is likely to increase as climate change modifies the frequency and severity of drought and wildfires (Ford et al., 2018; IPCC, 2018; Westerling et al., 2006). The increase in fire smoke will impose significant costs on society via higher health care costs, lower labor productivity (Adhvaryu et al., 2019; Borgschulte et al., 2018; Chang et al., 2019; Graff Zivin and Neidell, 2012; Zahran et al., 2017), and possible increased anxiety and psychological stress (Power et al., 2015; Sass et al., 2017). Our paper adds to this list of costs by highlighting the extent to which pollution can lead to aggressive behavior.

PM is a mixture of many different organic and inorganic chemical components (Austin et al., 2013; Craig et al., 2012; Naeher et al., 2007; Sillanpää et al., 2006; Valavanidis et al., 2008) and specific constituents of PM can lead to systemic inflammation that is associated with adverse health outcomes (Bell et al., 2009; Brook et al., 2010; Godleski et al., 2000; Libby et al., 2002; Nemmar et al., 2002; Pope III et al., 2004; Schwartz, 2001; Seaton

[3]The EPA pollution monitor data is limited to monitor locations and is not collected on all calendar days. Not all counties have a pollution monitor.

[4]Although most fire smoke plumes are visible from space, correlating observed smoke plumes with surface-level $PM_{2.5}$ is a notoriously difficult problem in the atmospheric sciences (Brey et al., 2018; Lassman et al., 2017). Satellite-observed smoke plumes may not affect surface-level $PM_{2.5}$. We ultimately develop a method to correct this measurement error and we describe this methodology in Section 3.

[5]The results are robust to county-by-year-by-season fixed effects.

et al., 1999; Zahran et al., 2017). Thus, regional differences in the measured effects may be attributable to regional differences in the composition of $PM_{2.5}$. However, our results indicate a lack of statistically significant differences across regions, indicating particulate matter composition is not a significant factor.[6]

Our research also relates to a relatively large and broad literature on criminal behavior (Anderson, 1999; Bishop and Murphy, 2011). Criminal activity is influenced by the probability of arrest (Becker, 1968), the outcome of Sunday night football games (Card and Dahl, 2011), seasonal variation in daylight (Doleac and Sanders, 2015), and increased oil and gas employment (James and Smith, 2017; Komarek, 2018). Other papers have identified a relationship between heat and crime (Blakeslee and Fishman, 2018; Field, 1992; Jacob et al., 2007; Mapou et al., 2017; Ranson, 2014). However, we are aware of only one published (Lu et al., 2018) and two currently unpublished manuscripts that identify a relationship between pollution and crime (Burkhardt et al., 2018; Herrnstadt et al., 2016).

Lu et al. (2018) document correlation between air pollutants and crime rates measured annually. While causal identification is challenging with annual data, they report positive correlations between air pollution and crime. Herrnstadt et al. (2016) exploit wind patterns to show that short-term increases in air pollution increase violent crime in Chicago and Los Angeles.[7] Burkhardt et al. (2018) use daily crime data from the FBI's National Incident Based Reporting System (NIBRS), combined with similar pollution and fire smoke plume data used in the present study, to identify the effect of daily variation in $PM_{2.5}$ on violent crime. The drawback of the NIBRS data is that counties are not required to report daily criminal activity, which leads to a selection problem and limits the geographic scope of analysis. Specifically, Burkhardt et al. (2018) evaluate the effect of changes in $PM_{2.5}$ on crime across only 561 counties with notably large exclusions such as New York, Chicago, and Los Angeles. However, the benefit of the NIBRS data is that it is reported at

[6]We should note that the lack of statistical significance across regions could be due to a mismatch between the Census Bureau regions used in this paper and regional PM composition, or other measurement error.

[7]Several other studies have used upwind pollution as a source of exogenous variation (e.g., Deryugina et al., 2016; Keiser et al., 2018; Moeltner et al., 2013).

the daily-level, which allows for more detailed temporal analysis.

Our study differs from and complements Herrnstadt et al. (2016) and Burkhardt et al. (2018) in three ways. First, we use data from 99% of all U.S. counties, which eliminates any potential selection problems. Second, our analysis evaluates regional and sociodemographic heterogeneity, which highlights important differences across the U.S. and begins to narrow in on the causal mechanisms driving this new result. Lastly, we find remarkably similar effects to those of Herrnstadt et al. (2016) and Burkhardt et al. (2018), corroborating these relatively new findings.

The remainder of the paper proceeds as follows. The following section outlines the data used in the paper and provides summary statistics and descriptions of the data cleaning process. Section 3 presents our econometric model and describes the identification assumptions. Section 4 presents our results, Section 5 provides a discussion, and Section 6 concludes.

2 Data

Our data is comprised of four main variables spanning every month between 2006-2015. First, the United States Federal Bureau of Investigation (FBI) maintains monthly crime counts by county via the Uniform Crime Reporting Program (UCR, 2004). The UCR covers the entire U.S. and reports consistent counts of violent crimes including aggravated assaults and robberies and property crimes including thefts/larceny and vehicle thefts.

Second, we merge the monthly-county crime data with surface-level $PM_{2.5}$ concentrations. The Air Quality System (AQS), which is managed by Environmental Protection Agency (EPA), is a network of federal, state, and tribal pollution monitors that measure ozone, $PM_{2.5}$, and other pollutants.[8] One limitation of the AQS is that not all counties contain pollution monitors, which results in spatial gaps in the data. To address these gaps, we use ordinary kriging to interpolate daily $PM_{2.5}$ concentrations for a 15 km grid

[8]The data is publicly available from `https://aqs.epa.gov/aqsweb/airdata/download_files.html`.

of the entire continental U.S. We calculate the mean $PM_{2.5}$ of all grid cells within a county, then take the average and maximum $PM_{2.5}$ measures for each county for each month of the sample.[9]

Third, we merge data on fire smoke plumes from the National Oceanic and Atmospheric Administration Hazard Mapping System (HMS). The HMS provides daily measures of smoke plumes based on satellite imagery for the entire U.S. (HMS, 2018; Rolph et al., 2009; Ruminski et al., 2006). Smoke plumes are outlined and defined by trained analysts that work alongside and review automated algorithms that can detect plumes in satellite imagery. The publicly available data includes polygons of all relevant smoke plumes for all days since August 5, 2005. To be consistent with the kriged pollution monitor data, we grid the smoke plume data and assign a value of 1 if a particular county contained a grid box that was under a smoke plume for each day of the month of the sample and 0 if not. We then count the number of days within a month that a county was under a smoke plume. Figure 1 displays the spatial distribution of the number of days in our sample covered by a smoke plume using the gridded HMS data or the raw unadjusted HMS data. The Midwest is lightest in color with up to 15% of the days in the sample covered by a smoke plume.

A key feature of smoke plumes is that they can be generated by fires that originated hundreds or thousands of miles from the affected county. This can produce an exogenous increase in pollutant levels, particularly $PM_{2.5}$ (Brey et al., 2018; Ruminski et al., 2006). However, local wind and weather patterns can significantly impact how smoke plumes are transported. For instance, smoke plumes are often transported in the upper atmo-

[9]Kriging is a geostatistical interpolation method. Kriged surfaces have been used in previous research to estimate air pollution exposures (Janssen et al., 2008; Jerrett et al., 2005; Lassman et al., 2017) and ordinary kriging has been shown to effectively predict air pollution across large-geographic areas (Beelen et al., 2009). Universal kriging or other predictive models that incorporate land use or satellite based covariates provide improved prediction performance and more spatially specific surfaces (Beelen et al., 2009; Di et al., 2016; Mercer et al., 2011; Young et al., 2016). For reference, we use all available federal reference method (FRM) and FRM-corroborated daily $PM_{2.5}$ observations in the EPA AQS monitor network. We then krige the observations to a 15 km grid, which produces a gridded estimate of daily-average $PM_{2.5}$ concentrations for each day during the study period. Kriging parameters are as follows: sill = 2.6, range = 8.5, nugget = 0.1. The parameters were determined using a k-fold cross validation with 10 folds, optimizing R^2 while also maintaining minimal mean bias and mean absolute error.

sphere and may not significantly affect surface-level air quality, despite being present in satellite imagery (Brey et al., 2018; Ford et al., 2017; Rolph et al., 2009). This discrepancy is a source of measurement error: satellite based smoke plumes reported by the HMS are often poor predictors of surface level air quality. Burkhardt et al. (2018) develops a method to address this measurement error using surface-level pollution measurements to probabilistically detect whether the smoke plume affected human exposure. We define the modified variable as the *adjusted HMS variable*. Figure 2 shows the spatial distribution of the fraction of *neighbor-adjusted* smoke days in our sample (the adjustment procedure is outlined in Section 3). While the highest frequency of smoke plume days reported by the raw HMS occurs over the Midwest (Figure 1), the adjusted HMS smoke plume data indicate that most of that smoke in the Midwest does not affect surface level $PM_{2.5}$ (Figure 2). Importantly, Figure 2 shows that the distribution of smoke at the surface level is dramatically different from the distribution of smoke higher in the atmosphere across the U.S. We aggregate the smoke plume data to the county-monthly level and merge it with the crime and pollution data.

Our fourth dataset contains weather information from the Parameter-elevation Regressions on Independent Slopes Model (PRISM, 2017). We again utilize gridded data on daily maximum temperatures (Celsius), daily minimum temperatures (Celsius), and daily precipitation (millimeters) at a 4 kilometer resolution. We calculate the monthly county-level maximum and minimum temperature and average rainfall as the average of all grid cells within a county for each month in the data.

We collect county-level annual demographic and socioeconomic data from the American Community Survey (US Census, 2017). We investigate the heterogeneity of our main effect of $PM_{2.5}$ on violent crime by county median household income (Income), population, percent of population white (% White), percent of population with a Bachelors degree (% Bachelors), percent of population living under the poverty threshold (% Poverty), and median age in the county (Age).

2.1 Summary Statistics and Data Cleaning

Our data covers 2,977 counties (99% of all U.S. counties) in the U.S. from 2006-2015. Summary statistics for the variables used in estimation are displayed in Table 1. Crimes are presented as monthly counts. We drop observations with negative crime counts for each category of crime or counts above the 99th percentile of crimes for each category of crime. This drops 3,650 observations or 1.1% of our sample. We do this because, for example, several counties in the raw FBI data report more than 14,000 violent crimes in a given month. These are most likely annual counts that are misreported as monthly counts.[10] We also drop counties that only report crimes on an annual basis, biannual basis, or quarterly basis. After this cleaning, the average number of violent crimes per county per month is 20.31 with a maximum of 514.

Sixty-three percent of violent crimes are assaults on average. There are 160.5 property crimes per month on average in our sample, 69% of which are larcenies or thefts. The monthly mean maximum and minimum temperatures are 18.67 and 6.28 degrees Celsius, respectively. The average monthly precipitation is 2.78 mm. The mean of the monthly average $PM_{2.5}$ level is 9.42 $\mu g/m^3$ with a minimum of 0.01$\mu g/m^3$ and a maximum of 87.93 $\mu g/m^3$. The minimum occurred in Tehama County, California in May 2014 while the maximum occurred in Lemhi County, Idaho in September 2012. In 2012, Idaho and Montana experienced a severe fire season with over 1.1 million acres burned.[11] The mean of the monthly maximum $PM_{2.5}$ level is 19.29 $\mu g/m^3$ with a minimum of 2.73 $\mu g/m^3$ and a maximum of 337.39 $\mu g/m^3$. The minimum occurred in Archuleta County, Colorado in February 2013, while the maximum occurred in Okanogan county, Washington in August 2015. The high $PM_{2.5}$ levels were due to wildfire smoke.

Finally, we provide summary statistics for the two HMS smoke plume count variables and the demographics. The mean of the raw HMS variable is 2.78, which suggests that

[10]For example, the city of Chicago, which spans 12 counties, had a total of 17,400 violent crimes in 2015. This implies an average of only 1,450 violent crimes per month across the 12 counties in the nation's most violent city. These statistics were downloaded from the Chicago police department here.

[11]https://www.claimsjournal.com/news/west/2012/11/07/216957.htm

a county is covered by a smoke plume for 2.78 days out of a given month, on average. The maximum value is 31 indicating that a smoke plume was present above at least one county for an entire month. The neighbor-county adjusted HMS variable is lower, at 0.46. The HMS satellite based smoke plume correction procedure is described in Section 3 below.

3 Model and Identification

We develop a model to investigate the impact of $PM_{2.5}$ on aggressive behavior as measured by crime. Our model is as follows:

$$\log[E(C_{ct}^{j})] = \gamma^{j} PM25_{ct} + \mathbf{X}_{ct}\boldsymbol{\beta}^{j} + \phi_{cy} + \xi_{m} + \hat{\nu}_{ct}, \tag{1}$$

where C_{ct}^{j} is the crime count of crime type j in county c in month t (an observation is a county-month), $PM25_{ct}$ in our primary analysis is the monthly mean $PM_{2.5}$ in μg/m^3 in county c in month t, $\mathbf{X}_{ct}$ includes average monthly maximum temperature, monthly minimum temperature, and monthly precipitation, ϕ_{cy} is a county-by-year fixed effect, ξ_m is a month fixed effect, and $\hat{\nu}_{ct}$ is a control function. All estimates are performed using Poisson regression as C_{ct}^{j} is a non-negative count variable. All standard errors are clustered at the county-level to address within county correlation in the error term.

We use monthly mean $PM_{2.5}$ as our main measure of $PM_{2.5}$ rather than monthly maximum $PM_{2.5}$. If fire smoke plumes affect surface level $PM_{2.5}$ within a county for multiple days within a month, the monthly average more accurately captures the exposure compared to the monthly maximum. This is important because our instrument, described below, is the number of days a county is affected by a fire smoke plume in a given month. As a robustness check, we present our primary results using the monthly maximum $PM_{2.5}$ measure in Table 7.

Pollution is likely endogenous in Equation 1. For example, $PM_{2.5}$ and crime are likely correlated with county specific unobservables such as urban status, population density, county or state level policies, and industrial and employment activity. If unaddressed, these unobservables will lead to biased estimates of γ. We address this endogeneity in two ways. First, we include county-by-year fixed effects to control for county specific unobservables that are either constant within a year or may vary from year to year. Examples of the former include urban status, long-term pollution laws, and general sociodemographics. Examples of the latter include changes in population density, police enforcement and air pollution concentrations over time. We also include month fixed effects to control for seasonal variation in pollution and crime as well as other confounders such as seasonal allergens. Importantly, we show that much of the endogeneity is addressed by our fixed effects.

Second, despite the inclusion of county-by-year and month fixed effects, $PM25_{ct}$ may still be endogenous. For example, monthly average $PM_{2.5}$ is an imperfect measure of short-term pollution exposure. As such, Equation 1 likely suffers from measurement error. Likewise, there may be county specific cyclical variation in crime and/or $PM_{2.5}$ that is not fully captured by month fixed effects that are constant across regions. We use a control function to address this potentially remaining endogeneity in pollution. Control functions perform the same function as instrumental variables estimation and are easily implemented in nonlinear models such as the Poisson routine used in the present setting. Specifically, we instrument $PM25_{ct}$ with the count of the number of days county c is affected by a fire-smoke plume in month t. To be precise, our smoke plume and pollution data are collected at the daily level. Thus, on any given day in our sample, HMS=0 if a smoke plume is not present over location c and HMS=1 if a smoke plume is present over location c. Crimes are measured at the monthly level so we aggregate the HMS variable to the monthly level. Our control function assumption, which is identical to an instrumental variables assumption, is that smoke plumes, which can be generated thousands of miles away, are correlated with surface-level $PM_{2.5}$, but do not directly influence crime levels.[12] The control function takes the following form :

[12]To be sure, in Table 6, we present a robustness check in which we drop observations where a fire was burning in a county in a particular month.

$$PM25_{ct} = \beta_1 HMS_{ct} + \mathbf{X}_{ct}\boldsymbol{\beta}^{CF} + \phi_{cy} + \xi_m + \nu_{ct}. \tag{2}$$

Equation 2 includes all second stage regressors and fixed effects included in Equation 1, and is estimated via Ordinary Least Squares (OLS). The smoke plume instrument is termed, HMS_{ct}, and is described in the following paragraphs.

It is well understood among atmospheric scientists that smoke plumes observed via satellite imagery (i.e., HMS variables) are poor predictors of surface level $PM_{2.5}$. This is because smoke plumes that may have been generated hundreds or thousands of miles away are often transported several kilometers above the Earth's surface (Brey et al., 2018; Larsen et al., 2018). Consequently, when a smoke plume is observed in satellite imagery above a pollution monitor ($HMS_{ct} = 1$), the surface-level pollution monitor will often not report elevated pollution levels. In other words, despite the presence of a smoke plume in the upper atmosphere, surface-level pollution is not affected. We follow a procedure, similar to the methodology used by Brey and Fischer (2016) to retain only surface-level smoke plumes that impact surface-level air quality.

To adjust the HMS variable, we first calculate county-specific background $PM_{2.5}$ means (three month seasonal mean) and standard deviations using our daily $PM_{2.5}$ data. We calculate these means and standard deviations on non-HMS smoke days (days in which a smoke plume is not present in the raw satellite imagery). We then correct the discrepancy between the HMS variable and the surface-level $PM_{2.5}$. Our adjustment procedure isolates days when smoke plumes significantly impacted surface-level $PM_{2.5}$. Our method adjusts the HMS variable in county c on day t using the $PM_{2.5}$ and HMS measure of the nearest neighboring $PM_{2.5}$ county centroid. For example, suppose we have a neighboring county $k \neq i$. We set $HMS_{ct} = 0$ in time period t if $HMS_{kt} = 1$ but $PM_{2.5}$ at county centroid k is less than 1.64 standard deviations from the background mean of county centroid k. Likewise, we set $HMS_{ct} = 0$ if $HMS_{kt} = 0$ in all neighboring counties.[13] This variable is called the neighbor-adjusted HMS variable.[14] We then aggregate the neighbor-county adjusted HMS variable to the county-monthly level.[15]

The validity of the neighbor-adjusted HMS variable as an instrument for $PM_{2.5}$ rests on two assumptions. First, because we use $PM_{2.5}$ in county k to adjust the HMS variable in county c, we must assume that a smoke plume affecting surface level $PM_{2.5}$ in location c will also affect surface level $PM_{2.5}$ in location k. We believe this is a valid assumption as smoke plumes often span many contiguous county boundaries. Though the neighbor-adjusted HMS variable suffers from a new source of measurement error, this new measurement error is not as detrimental to our estimates as the measurement error in the unadjusted HMS variable. Second, we must assume that the background mean $PM_{2.5}$ in county c and the background mean $PM_{2.5}$ in county k are uncorrelated, conditional on our fixed effects and control variables. If these assumptions are valid, then the neighbor-adjusted HMS variable remains exogenous and is a valid instrument for $PM_{2.5}$ in county c.[16]

[13]This means that $PM_{2.5}$ on a particular day must be elevated above the 95th percentile of the county-specific background $PM_{2.5}$ mean, assuming a normal distribution, for the own-county adjusted HMS variable to equal one.

[14]Surface-level $PM_{2.5}$ is less than 1.64 standard deviations of the within-county background mean on 83% of the days in which a smoke plume is present (HMS=1 days). This means that smoke plumes observed in satellite imagery only increase surface-level $PM_{2.5}$ more than 1.64 standard deviations above the mean 17% of the time, highlighting the need for this adjustment procedure.

[15]The spatial distribution of the adjusted data is displayed in Burkhardt et al. (2018). We also show the spatial distribution of the adjusted data relative to the unadjusted data in Burkhardt et al. (2018). We find no discernible patterns in the areas that are adjusted.

[16]In Burkhardt et al. (2018), we test the latter assumption and find that the background means between county c and county k have a correlation coefficient of 0.32. Thus, the two are not perfectly correlated. Similar studies such as Keiser et al. (2018) and Deryugina et al. (2016) have used upwind air quality as an instrument for within county air quality. In these papers, the authors instrument pollution in a given county i with pollution in an upwind neighboring county. Our IV strategy is slightly different since we observe whether a county was covered by a smoke plume but not the elevation of the plume. We exploit the proximity of the neighboring county for smoke exposure (requiring that both counties lie under the same plume) but assume that non-smoke factors impacting PM2.5 in the neighboring county are exogenous to county i. Our instrument thus depends on correlation in smoke plumes across counties, not correlation in PM2.5 across counties, as an upwind analysis would utilize. Smoke plumes travel hundreds to thousands of miles and span multiple neighboring counties. Thus, an analysis that limits the sample to upwind counties only would likely produce virtually identical results precisely because a given smoke plume is usually affecting many contiguous counties, both upwind and downwind. Moreover, Bondy et al. (2018) study the relationship between daily pollution exposure and crime in London for a two year period. Like ours, their primary identification strategy relies on a series of high-dimensional fixed effects. However, they instrument pollution with wind direction as a robustness check. While wind direction is likely uncorrelated

4 Results

In the following section, we present a series of results. First, we present several specifications of Equation 1, using violent crimes as the dependent variable, which demonstrate the robustness of our results and highlights the importance of the county-by-year fixed effects. We also discuss the first stage control function estimates to highlight the importance of adjusting the HMS variable. Second, we estimate our model using assaults and other non-violent crimes as alternative outcome variables. We then explore the potential mechanisms behind our primary results by exploring regional and sociodemographic heterogeneity in the primary effects. Lastly, we present robustness checks. All regressions are estimated in Stata version 14.

4.1 Primary Results

The results of estimating Equation 1 with various sets of fixed effects and control functions are displayed in Table 2. The dependent variable in each column is violent crimes. Columns 1 and 2 present estimates without control functions. The specification presented in Column 1 includes county, year, and month fixed effects while the specification presented in Column 2 includes county-by-year and month fixed effects. If $PM_{2.5}$ is endogenous, and crime rates and $PM_{2.5}$ are positively correlated with unobservables that vary over time within counties, then the coefficient estimates should decline from Column 1 to Column 2. Indeed, we find that the inclusion of the county-by-year fixed effect in Column 2 slightly reduces the coefficient on $PM_{2.5}$. For this reason, we use county-by-year and month fixed effects in all further specifications.[17]

Columns 3-4 of Table 2 replicate the specification in Column 2 adding two variations of the control function. The instrument used in Column 3 is the unadjusted or raw HMS variable. Brey et al. (2018), Burkhardt et al. (2018), and our first stage estimates presented

with daily crime, in their preferred instrumental variables model, the first stage F-statistic is fairly small (around 13) indicating that wind direction is not the strongest of instruments for daily air pollution.

[17]We tried other sets of fixed effects such as county-by-year-by-season but these absorbed too much of the variation in $PM_{2.5}$ and crimes.

in Table A.2 show the raw HMS variable is a poor predictor of surface-level $PM_{2.5}$, which introduces measurement error. Column 3 of Table 2 illustrates the consequences of this measurement on our primary estimates. When monthly average $PM_{2.5}$ is instrumented with the count of days a county is covered by a smoke plume in the raw HMS data, the control function is statistically insignificant, rendering the primary coefficient on $PM_{2.5}$ also statistically insignificant. This result can be attributed to the measurement error between the raw HMS data and surface-level $PM_{2.5}$.[18]

Column 4 instruments $PM_{2.5}$ using the neighbor-county adjusted HMS variable. In contrast to the model presented in Column 2, the control function and the coefficient on $PM_{2.5}$ are highly statistically significant in this model. Notably, the coefficients on $PM_{2.5}$ presented in Columns 3-4 are larger than the non-control function estimate presented in Column 2. One possible explanation is that monthly average $PM_{2.5}$, the measure used in each of these models, is an imperfect measure of daily changes in $PM_{2.5}$. As such, the correlation estimates presented in Columns 1 and 2 are subject to classical measurement error, which is corrected to some degree by the control functions. Thus, our preferred specification is the neighbor-adjusted HMS control function presented in Column 4, and we use this specification in all of the remaining estimates in the paper.

Next we investigate the effect of changes in $PM_{2.5}$ on other categories of crime. Table 3 displays the results of estimating our primary model (Column 4 of Table 2) using assaults, other violent crimes (violent minus assault), property crimes, robberies, and larceny/thefts as dependent variables. Columns 1 and 2 indicate that the violent crime effect presented in Table 2 is driven exclusively by changes in assaults. Columns 3, 4,

[18]The first stage control function estimates are presented in Table A.2 in the Appendix. Column 1 of Table A.2 shows the first stage using the raw HMS variable and Column 2 the first stage estimates using the neighbor-adjusted HMS variable. The HMS variables in both models is statistically significant, however, the coefficient in Column 2 is seven times larger than the coefficient in Column 1. Indeed, the model in Column 1 suggests that an additional HMS day increases monthly average $PM_{2.5}$ by only 0.10 $\mu g/m^3$. This is a very small amount given the mean $PM_{2.5}$ level is 9.42 $\mu g/m^3$. In contrast, the model in Column 2 suggests that an additional HMS day increases the monthly average $PM_{2.5}$ by 0.73 $\mu g/m^3$. Given these findings and our discussion in Section 3, we are confident that the adjusted HMS variable produces a stronger instrument than the raw HMS variable. Estimates using an own-county adjusted HMS variable are similar. Two-stage least squares estimates of the model produce Cragg-Donald weak identification F-statistics of 9,930 for the raw HMS variable and 68,000 for the adjusted HMS variable, respectively.

and 5 indicate changes in $PM_{2.5}$ are not significantly correlated with property crimes, robberies, or thefts. In fact, the coefficients in these three columns are not only statistically insignificant but are indicative of null estimates when compared to the magnitude of the effect presented in Column 1.[19] Overall, the results presented in Tables 2 and 3 align with the findings of Herrnstadt et al. (2016) and Burkhardt et al. (2018).

4.2 Heterogeneity in The Treatment Effect

We now turn to evaluating heterogeneity in the treatment effect. First, we generate dummy variables for nine regions of the U.S. defined by the Census Bureau. The Census Bureau regions include New England, Mid-Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, and Pacific. The states included in each region are listed in the Appendix (Section 9). We interact the $PM_{2.5}$ variable with the region dummy variables (New England is the base case). If the composition of $PM_{2.5}$ throughout the U.S. is homogeneous, and the effects we estimated above are driven purely by physiological factors, then we hypothesize the treatment effect should be uniform across the U.S.

Table 4 displays the estimates of our regional analysis. The results indicate no statistical differences across Census Bureau regions of the U.S.[20]

[19]The sample size differs between specifications due to the number of zeros or missing values in the dependent variables within fixed effects clusters.

[20]Results using Bureau of Economic Analysis regions are similar. The effect is statistically insignificantly largest in New England, the omitted category, which is consistent with our demographic estimates below. One caveat of these results is that the effects may be heterogeneous at a different geographic scale than the Census Bureau regions or our data may lack sufficient power to identify regional heterogeneity.

The results presented in Table 4 suggest virtually no differences in treatment effects across the U.S. A possible explanation for the lack of regional heterogeneity is that pollution affects behavior through physiological mechanisms, which are uniform in geographic scope, but are modified by socioeconomic conditions. To test for heterogeneous effects due to socioeconomic differences, we generate dummy variables indicating quartiles of county-level demographics and interact these dummy quartiles with $PM_{2.5}$.

The results of the demographic heterogeneity analysis are presented in Table 5. Column 1 suggests that the effects are largest (statistically insignificant) in areas with the highest median household income (F-statistic p-value of joint significance for four presented coefficients is 0.009). Column 2 provides evidence that the effects are largest (again, statistically insignificant) in the largest metropolitan areas. The coefficients on each of the population quartile interactions are negative and jointly statistically significant with the coefficient on $PM_{2.5}$ (F-statistic p-value = 0.007). This result is expected given there are more crimes in more populated areas. However, the results remain significant for regions with low populations. Column

We look at summary statistics of the demographic variables by Census Bureau region to compare the results in Table 5 to the regional estimates in Table 4. Summary statistics are presented in the Appendix (Section 9). The results in these two tables indicate the effect is moderately larger in New England and in wealthier, whiter, and older counties. Importantly, the summary statistics in Table A.1 in the Appendix indicate that New England has the largest fraction of the population that is white, has the highest median age, and the lowest poverty rate. Overall, our heterogeneity results indicate the most important explanatory factor in the relationship between pollution and crime is age, and the results are not ameliorated by higher incomes.

4.3 Robustness Checks

In the following section, we present several robustness checks including adding flexible functions of temperature and alternative measures of pollution. In each of the following specifications, we focus on violent crimes as the dependent variable.

Table 6 presents our main robustness checks. Column 1 includes and interaction term between pollution ($PM_{2.5}$) and the monthly average maximum temperature. The results suggest that the effect of pollution is decreasing in maximum temperature but not significantly so. In Column 2, we replace the monthly average maximum temperature with a restricted cubic spline of monthly average maximum temperature. The coefficient of interest is largely unchanged, going from 0.0053 in Table 2 to 0.0057 in this alternative specification.

Wildfires can be extremely disruptive in the counties in which they burn. Thus, one might be concerned that our results are driven by counties in which a wildfire is burning.

3 indicates that the effect is stronger in counties with a higher fraction of the population that is white. The effect is 50% smaller in counties in the first quartile for fraction of the population that is white. Column 4 indicates that average educational attainment does not significantly impact the effect of pollution on aggressive behavior. Column 5 indicates that the effect is generally largest in the second quartile of poverty rates, or the effect is largest in relatively wealthy counties, consistent with the income effects presented in Column 1. Finally, column 6 indicates that the effect is statistically significantly largest in counties with older populations. The latter result indicates that older populations are more susceptible to physiological impacts of pollution.

For instance, it might be the case that more looting and confrontation occurs in counties in which an evacuation order is in place. To test this, we estimate our model dropping observations in which a fire is burning within a county in a given month.[21] The results are displayed in Column 3 of Table 6. The coefficient on $PM_{2.5}$ declines slightly from our main estimates, which could be due to an evacuation effect or simply the different sample. Importantly, the coefficient remains statistically significant.

Finally, we re-estimate Table 2 replacing the monthly average of $PM_{2.5}$ (over all days within a county-month) with the monthly maximum of $PM_{2.5}$ (over all days within a county-month). The two measures capture different aspects of the distribution of $PM_{2.5}$ within a county within a month. The average better reflects periods in which the county has elevated $PM_{2.5}$ levels for multiple days within a month, while the maximum better reflects periods in which the county may have only had one extreme $PM_{2.5}$ event day. The results are presented in Table 7. Although the point estimates on $PM_{2.5}$ differ from those presented in Table 2 (which can be attributed to the different measure of $PM_{2.5}$), the results are qualitatively identical.

5 Discussion

The results in this paper indicate that changes in $PM_{2.5}$ affect the propensity for violent crimes on a population level with a emphasis on assaults. Assaults are likely indicative of impulsive and aggressive behavior. Thus, our estimates are consistent with recent work in epidemiology that suggests fine particulate matter air pollution ($PM_{2.5}$) can induce biological processes, like systemic inflammation, which could potentially exacerbate aggressive behavior (Brook et al., 2004; Cunningham et al., 2009; Donaldson et al., 2001). Furthermore, we find no relationship between $PM_{2.5}$ and non-violent property crimes, which are not generally crimes of passion and thus not likely to be driven by the same impulsive mechanisms.

[21] Short (2017) reports the latitude and longitude of wildfire ignitions as well as the discovery and end dates. We exclude county-days with an active fire burning.

Our primary results are also consistent with Herrnstadt et al. (2016) and Burkhardt et al. (2018). Herrnstadt et al. (2016) uses different data and a different identification strategy while Burkhardt et al. (2018) uses daily data but evaluates a smaller geographic sample. Together, our papers provide compelling evidence of a previously overlooked cost of pollution.

A key feature of our data is that it spans the entire U.S., allowing us to explore several dimensions of effect heterogeneity. The results presented in Section 4.2 indicate no statistical differences in the effects across regions. However, we find strong statistical differences across age brackets, which is consistent with older populations being more susceptible to changes in air pollution. While our data does not allow us to identify the precise physiological processes driving our primary results, our results point to an important and previously unknown impact of pollution that is present in all parts of the country. Our findings also suggest further research on the modifying factors behind the estimated effects is warranted. For instance, although our data indicates no statistical differences across geographic regions of the U.S., the species of $PM_{2.5}$ varies temporally and geographically and these differences in species may present different neurological toxicities. Future research should thus explore differences in the relationship between pollution exposure and behavioral outcomes by PM speciation.

The estimates in this paper are not without limitations. Our data are monthly averages of $PM_{2.5}$ and are imperfect measures of short-term or acute exposure to changes in $PM_{2.5}$. For instance, using data on daily pollution and crime, Burkhardt et al. (2018) show that the effect of changes in $PM_{2.5}$ on violent crime is highly contemporaneous with virtually no effect even in 1 day lags. Thus, we expect measurement error is present in $PM_{2.5}$ in Equation 1. An additional concern is that we do not have $PM_{2.5}$ speciation data, which could be an important omitted variable in the present analysis.

6 Conclusion

This paper identifies the effect of changes in pollution on criminal activity at the monthly level across the entire U.S. We have three primary data sources at the monthly-county level spanning 2006-2015. First, we use $PM_{2.5}$ measures from Lassman et al. (2017). Second, we observe monthly crime counts from the FBI UCR program. Lastly, we use NOAA's HMS smoke plume data to generate an instrument for $PM_{2.5}$. Our identification strategy employs a series of high-dimensional fixed effects and a control function to address endogeneity in $PM_{2.5}$.

Our primary finding is that a 1 $\mu g/m^3$ increase in the monthly average $PM_{2.5}$ increases monthly violent crime rates by 0.53%, nearly all of which is driven by increases in assaults. This estimate translates to an additional 327 additional violent crimes per month on average across the contiguous U.S. Alternatively, changes in $PM_{2.5}$ have no statistically significant effect on other violent or non-violent crimes, which indicates that an increase in $PM_{2.5}$ can act as a short-term irritant, which can increase the propensity for violent behavior. Importantly, we find that the effects are present across the entire U.S. with differences by age bracket. Our results are robust to a variety of tests and alternative specifications. Overall, our results are consistent with previous estimates and highlight a key social cost of pollution that is currently absent from policy discussions.

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7 Tables

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Violent Crimes	20.31	52.08	0	514	328165
Assaults	12.88	30.31	0	291	323896
Robbery	4.64	15.77	0	187	239712
Property Crimes	160.49	349.46	0	3252	323116
Larceny/Theft	111.34	237.59	0	2140	312659
Mean Max Temperature (C)	18.62	10.40	-14.23	43.23	328165
Mean Min Temperature (C)	6.28	9.76	-27.26	28.73	328165
Mean Precipitation (mm)	2.78	2.076	0	35.59	328165
Mean $PM_{2.5}$ ($\mu g/m^3$)	9.42	3.25	0.01	87.93	328165
Max $PM_{2.5}$ ($\mu g/m^3$)	19.29	7.90	2.73	337.39	328165
Raw HMS	2.78	4.67	0	31	328165
Neighbor Adjusted HMS	0.46	1.31	0	26	328165
Income	43386.85	11174.82	18869	112021	328165
Population	77436.23	157356.00	60	3156440	328165
% White	79.53	18.57	2.1	99.20	328165
% Bachelors	20.29	8.74	1.9	64.20	328165
% Poverty	15.37	6.31	0	52.38	328165
Median Age	40.41	4.98	21.6	63.8	328165

Notes: All crimes reported as counts per county per month. HMS variables are count variables. For example, the mean of the raw HMS variable indicates that the average county is covered by a smoke plume for 2.7 days a month in the sample. Demographic Summary Statistics by region are reported in Table A.1 in the Appendix.

Table 2: Primary Violent Crime Results

	(1)	(2)	(3)	(4)
$PM_{2.5}$	0.0011*	0.0009**	0.0051	0.0053***
	(0.0006)	(0.0004)	(0.0035)	(0.0015)
Mean Max Temp	0.0051***	0.0056***	0.0064***	0.0064***
	(0.0008)	(0.0007)	(0.0010)	(0.0007)
Mean Min Temp	0.0043***	0.0041***	0.0035***	0.0034***
	(0.0010)	(0.0009)	(0.0009)	(0.0009)
Mean Precip	0.0011	0.0006	0.0018	0.0018*
	(0.0009)	(0.0009)	(0.0011)	(0.0010)
CF Residuals			-0.0043	-0.0050***
			(0.0035)	(0.0016)
year FE	Y			
month FE	Y	Y	Y	Y
county FE	Y			
county-year FE		Y	Y	Y
Instruments Used	None	None	HMS1	HMS2
N	328165	328165	328165	328165

Notes: Dependent variable is violent crimes in each specification. HMS1 is the raw HMS smoke plume variable. HMS2 is the nearest neighbor county adjusted HMS variable. CF residuals are control function residuals. Standard errors clustered at the county level. *** denotes significance at 1% level, ** at 5% level, * at 10% level.

Table 3: Other Crimes

	(1) Assault	(2) Other Violent	(3) Property	(4) Robbery	(5) Larceny
$PM_{2.5}$	0.0059***	0.0010	0.0007	0.0005	0.0007
	(0.0017)	(0.0015)	(0.0009)	(0.0018)	(0.0008)
Mean Max Temp	0.0091***	0.0025***	0.0063***	0.0021*	0.0064***
	(0.0008)	(0.0009)	(0.0007)	(0.0012)	(0.0007)
Mean Min Temp	0.0019*	0.0065***	0.0093***	0.0084***	0.0093***
	(0.0010)	(0.0009)	(0.0009)	(0.0012)	(0.0009)
Mean Precip	0.0014	-0.0000	0.0012**	0.0001	0.0005
	(0.0010)	(0.0008)	(0.0006)	(0.0010)	(0.0005)
CF Residuals	-0.0050***	-0.0019	-0.0011	-0.0030	-0.0007
	(0.0017)	(0.0016)	(0.0010)	(0.0018)	(0.0009)
county-year FE	Y	Y	Y	Y	Y
month FE	Y	Y	Y	Y	Y
N	323896	183924	313116	239712	312659

Notes: Each of the columns in this table use the specification from Column 5 of Table 2 but with alternative dependent variables. Other Violent is violent crimes less assaults. The instrument used to generate the control functions in all models is the nearest neighbor adjusted HMS variable. Standard errors clustered at the county level. *** denotes significance at 1% level, ** at 5% level, * at 10% level.

Table 4: Heterogeneity By Region of the U.S.

	(1)
$PM_{2.5}$	0.0074***
	(0.0024)
$PM_{2.5}$*1(Mid-Atlantic)	-0.0030
	(0.0021)
$PM_{2.5}$*1(East North Central)	-0.0017
	(0.0020)
$PM_{2.5}$*1(West North Central)	-0.0014
	(0.0023)
$PM_{2.5}$*1(South Atlantic)	-0.0019
	(0.0022)
$PM_{2.5}$*1(East South Central)	-0.0006
	(0.0025)
$PM_{2.5}$*1(West South Central)	-0.0018
	(0.0022)
$PM_{2.5}$*1(Mountain)	-0.0027
	(0.0020)
$PM_{2.5}$*1(Pacific)	-0.0027
	(0.0019)
month FE	Y
county-year FE	Y
N	328165

Notes: This table replicates our primary specification, Column 5 of Table 2, but interacts $PM_{2.5}$ with dummy variables for regions of the U.S. defined by the Census Bureau. The regions are outlined in Appendix 9. The omitted category is region 1, New England. The dependent variable is violent crimes. The regression includes temperature and precipitation controls as well as a control function. Standard errors clustered at the county level. *** denotes significance at 1% level, ** at 5% level, * at 10% level.

Table 5: Heterogeneity By Demographics

	(1)	(2)	(3)	(4)	(5)	(6)
Demographic Defining X	Income	Population	% White	% Bachelors	% Poverty	Age
$PM_{2.5}$*X First Quartile	-0.0007	-0.0076	-0.0040***	0.0005	0.0009	-0.0087***
	(0.0012)	(0.0049)	(0.0014)	(0.0010)	(0.0011)	(0.0026)
$PM_{2.5}$*X Second Quartile	-0.0014	-0.0039	-0.0016	0.0000	0.0020**	-0.0083***
	(0.0012)	(0.0042)	(0.0015)	(0.0010)	(0.0008)	(0.0027)
$PM_{2.5}$*X Third Quartile	-0.0007	-0.0006	-0.0011	0.0010	0.0009	-0.0062***
	(0.0008)	(0.0016)	(0.0015)	(0.0008)	(0.0009)	(0.0028)
$PM_{2.5}$	0.0059***	0.0058***	0.0080***	0.0051***	0.0043***	0.0130***
	(0.0018)	(0.0017)	(0.0019)	(0.0016)	(0.0015)	(0.0029)
month FE	Y	Y	Y	Y	Y	Y
county-year FE	Y	Y	Y	Y	Y	Y
N	328165	328165	328165	328165	328165	328165

Notes: This table replicates our primary specification, Column 4 of Table 2, but interacts $PM_{2.5}$ with quartiles of demographic variables. The omitted category in each specification is the fourth quartile interacted with $PM_{2.5}$. Therefore, the coefficient on $PM_{2.5}$ is the effect of an increase in $PM_{2.5}$ for counties in the fourth quartile of the demographic variable. For example, Column 1 includes interactions of $PM_{2.5}$ with quartiles of median household income and Column 2 includes interactions of $PM_{2.5}$ with quartiles of population. The dependent variable is violent crimes in each specification. The demographics in columns 3, 4, 5, and 6 are the fraction of the population that is white, the fraction of the population with a bachelors degree, the fraction of the population that is white, the fraction of the population in poverty, and the median age in the county. All regressions include temperature and precipitation controls as well as a control function. The coefficients are not shown for brevity. Standard errors clustered at the county level. *** denotes significance at 1% level, ** at 5% level, * at 10% level.

Table 6: Robustness Checks: Temperature and Fires

	(1)	(2)	(3)
	Violent	Violent	Violent
		temp spline	$fires = 0$
$PM_{2.5}$	0.0059***	0.0057***	0.0049***
	(0.0018)	(0.0015)	(0.0017)
$PM_{2.5}$*Mean Max Temp	-0.0000		
	(0.0000)		
Mean Max Temp	0.0067***		0.0064***
	(0.0009)		(0.0007)
Mean Min Temp	0.0034***	0.0035***	0.0039***
	(0.0009)	(0.0010)	(0.0009)
Mean Precip	0.0019*	0.0015	0.0011
	(0.0010)	(0.0010)	(0.0010)
CF Residuals	-0.0052***	-0.0050***	-0.0043**
	(0.0016)	(0.0016)	(0.0017)
county-year FE	Y	Y	Y
month FE	Y	Y	Y
N	328165	328165	322005

Notes: This table provides robustness checks for our primary specification, Column 5 of Table 2. Column 1 includes an interaction between $PM_{2.5}$ and Mean Maximum Temperature, Column 2 includes a restricted cubic spline of Mean Maximum Temperature, and Column 3 drops observations for a particular county in which a fire is burning within that county in the month of sample. The instrument used to generate the control functions in each specification is the nearest neighbor adjusted HMS variable. Standard errors clustered at the county level. *** denotes significance at 1% level, ** at 5% level, * at 10% level.

Table 7: Robustness Check: Primary Violent Crime Results Using Max $PM_{2.5}$

	(1)	(2)	(3)	(4)	(5)
Max $PM_{2.5}$	0.0007***	0.0007***	0.0016	0.0017***	0.0016***
	(0.0002)	(0.0002)	(0.0011)	(0.0004)	(0.0005)
Mean Max Temp	0.0050***	0.0056***	0.0058***	0.0059***	0.0059***
	(0.0008)	(0.0007)	(0.0008)	(0.0007)	(0.0007)
Mean Min Temp	0.0043***	0.0040***	0.0040***	0.0039***	0.0040***
	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Mean Precipitation	0.0010	0.0006	0.0010	0.0010	0.0010
	(0.0009)	(0.0009)	(0.0008)	(0.0009)	(0.0009)
CF Residuals			-0.0009	-0.0013***	-0.0011**
			(0.0011)	(0.0004)	(0.0004)
year FE	Y				
month FE	Y	Y	Y	Y	Y
county FE	Y				
county-year FE		Y	Y	Y	Y
Instruments Used	None	None	HMS1	HMS2	HMS3
N	328165	328165	328165	328165	328165

Notes: This table replicates our primary table, Table 2, using the county-month Maximum $PM_{2.5}$ rather than the county-month mean $PM_{2.5}$. Dependent variable is violent crimes in each specification. HMS1 is the raw HMS smoke plume variable. HMS2 is the own county adjusted HMS variable. HMS3 is the nearest neighbor county adjusted HMS variable. CF residuals are control function residuals. Standard errors clustered at the county level. *** denotes significance at 1% level, ** at 5% level, * at 10% level.

8 Figures

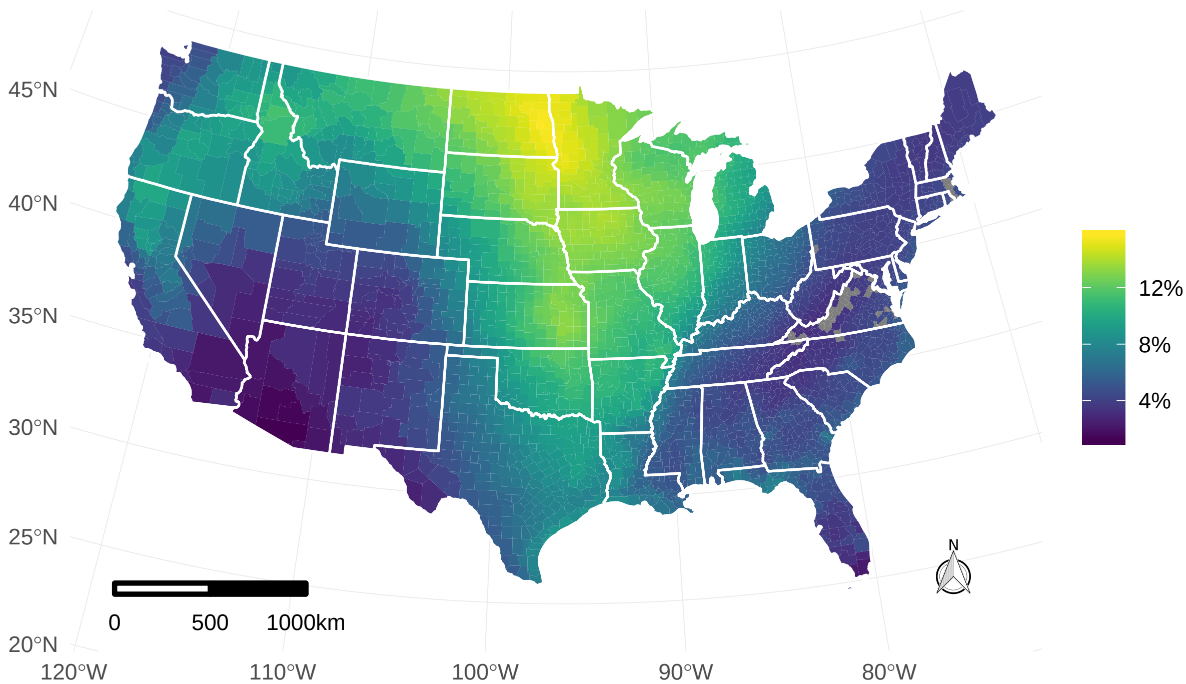

Figure 1: The color scale denotes the fraction of days in sample covered by a fire smoke plume observed from satellites and documented by the NOAA HMS smoke product (raw HMS variable).

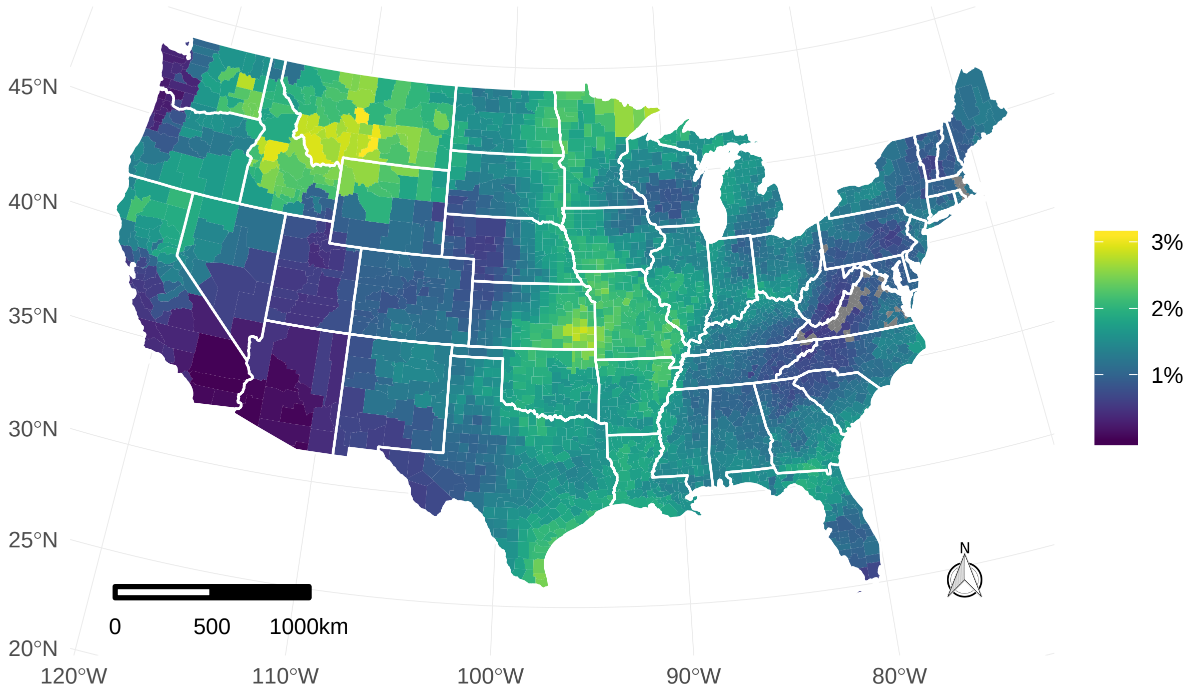

Figure 2: The color scale denotes the fraction of days in sample covered by the neighbor-adjusted fire smoke plume data (note the change in scale).

Online Appendix

9 Further Information on Regional Analysis

Census Bureau Divisions of the U.S.

- Division 1: New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, and Vermont)
- Division 2: Mid-Atlantic (New Jersey, New York, and Pennsylvania)
- Division 3: East North Central (Illinois, Indiana, Michigan, Ohio, and Wisconsin)
- Division 4: West North Central (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota)
- Division 5: South Atlantic (Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, District of Columbia, and West Virginia)
- Division 6: East South Central (Alabama, Kentucky, Mississippi, and Tennessee)
- Division 7: West South Central (Arkansas, Louisiana, Oklahoma, and Texas)
- Division 8: Mountain (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming)
- Division 9: Pacific (Alaska, California, Hawaii, Oregon, and Washington)

Table A.1: Summary Statistics

Division	**Income**	**Population**	**% White**	**%Bachelors**	**% Poverty**	**Median Age**	**Violent Crime Rate**	**Violent Crime Count**
New England	53734.44	183543.6	91.31	31.56	10.87	42.87	15.59	43.46
Mid-Atlantic	51653.74	208715	85.91	25.11	11.71	41.29	17.5	44.07
East North Central	46277.29	81021.83	90.83	19.84	12.88	41.01	16.4	18.42
West North Central	43374.26	35088.77	89.94	20.77	12.97	41.32	16.42	8.14
South Atlantic	42446.13	84885.37	70.8	19.62	16.95	40.44	26.57	23.24
East South Central	36610.9	46723.61	80.54	16.21	20.24	39.51	22.12	13.34
West South Central	39417.62	56722.61	65.42	17.29	18.52	38.92	26.73	19.44
Mountain	45441.32	61878.91	76.17	23.8	14.36	39.89	23.78	17.85
Pacific	48630.83	187896.8	72.94	24.05	14.36	40.81	24.15	55.37

Notes: Summary statistics of demographics by Census Bureau division. Violent crime rates are rates per 100,000 residents. Averages are taken over counties in the sample. Divisions are defined in Section 9.

10 First Stage Estimates

Table A.2: First Stage Regression

	(1)	(2)
Raw HMS	0.1077***	
	(0.0037)	
Neighbor-adjusted HMS		0.7253***
		(0.0113)
Mean Max Temp	-0.2436***	-0.2412***
	(0.0082)	(0.0077)
Mean Min Temp	0.1870***	0.1788***
	(0.0121)	(0.0115)
Mean Precip	-0.2713***	-0.2446***
	(0.0071)	(0.0065)
county-year FE	Y	Y
month FE	Y	Y
R-squared	0.616	0.669
N	328165	328165

Notes: Standard errors clustered at the county level. *** denotes significance at 1% level, ** at 5% level, * at 10% level.