Journal of Environmental Economics and Management 98 (2019) 102267

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

The effect of pollution on crime: Evidence from data on particulate matter and ozone

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ARTICLE INFO

Article history:
Received 12 March 2019
Revised 23 September 2019
Accepted 23 September 2019
Available online 30 September 2019

JEL classification codes:
Q53

Keywords:
Crime
Air pollution
Wildfire smoke

ABSTRACT

We estimate the effect of short-term air pollution exposure ($PM_{2.5}$ and ozone) on several categories of crime, with a particular emphasis on aggressive behavior. To identify this relationship, we combine detailed daily data on crime, air pollution, and weather for an eight-year period across the United States. Our primary identification strategy employs extremely high dimensional fixed effects and we perform a series of robustness checks to address confounding variation between temperature and air pollution. We find a robust positive effect of increased air pollution on violent crimes, and specifically assaults, but no relationship between increases in air pollution and property crimes. The effects are present in and out of the home, at levels well below Ambient Air Pollution Standards, and $PM_{2.5}$ effects are strongest at lower temperatures. The results suggest that a 10% reduction in daily $PM_{2.5}$ and ozone could save \$1.4 billion in crime costs per year, a previously overlooked cost associated with pollution.

1. Introduction

Links between pollution exposure and health outcomes have been established across a broad range of disciplines. Epidemiological and toxicological studies demonstrate a strong evidence base for a wide-range of short- and long-term health effects associated with exposure to airborne particulate matter (PM) (Archsmith et al., 2018; Di et al., 2017a,b; Pope and Dockery, 1999; Pope III and Dockery, 2006; Seaton et al., 1995). Research in economics demonstrates that exposure to air pollution can have adverse effects on health (e.g., Currie et al., 2014; Deryugina et al., 2016; Schlenker and Walker, 2016), cognitive function (e.g., Bishop et al., 2018; Graff Zivin and Neidell, 2013, 2012; Lavy et al., 2014), and labor productivity (e.g., Borgschulte et al., 2018; Graff Zivin and Neidell, 2012; Hanna and Oliva, 2015), and can impose large costs on individuals and society (Anderson, 1999; Bishop and Murphy, 2011).

The mechanisms that link long-term air pollution exposure to adverse health outcomes have often been evaluated for chronic disease, respiratory problems, and mortality outcomes (Dockery et al., 1993; Glantz, 2002; Pope III et al., 2002;

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https://doi.org/10.1016/j.jeem.2019.102267
0095-0696/

Samet et al., 2000; Schwartz, 2001). More recent evidence suggests that these same mechanistic pathways also have short-term effects on cognitive skills development, the expression of behaviors (e.g. aggressive, anti-social) associated with criminal or violent activities (Kioumourtzoglou et al., 2017; Lu et al., 2018), and anxiety (Power et al., 2015). However, despite a growing concern that air pollution exposure may be linked to aggressive behavior and criminal activity at a population level, we are aware of only one published study that attempts to identify this relationship (Lu et al., 2018).[1]

In this paper, we use a unique identification strategy to study the effect of short-term exposure to air pollution on aggressive behavior at a national scale. To do so, we combine two highly detailed datasets. First, we use data on criminal activity from the National Incident Based Reporting System (NIBRS) managed by the Federal Bureau of Investigation (UCR, 2004). Our final dataset contains incident-level crime reports for over fifty categories of crime spanning 397 counties, or 28.3% of the US population, between 2006 and 2013. The high spatio-temporal resolution of the data allows us to study the effect of short-term exposure to $PM_{2.5}$ and ozone on violent crimes, which we show is a key social cost of pollution that has heretofore been absent from policy discussions.[2]

Second, we merge the crime data with daily-county level air pollution ($PM_{2.5}$ and ozone) measurements spanning the entire US from 2006 to 2013. Pollution monitor data recorded by the US Environmental Protection Agency (EPA) is limited to monitor locations and is not collected on all calendar days. We use interpolated measures of $PM_{2.5}$, which provide gridded estimates (15 km grid) of $PM_{2.5}$ over the entire United States for every day of the 2006–2013 period (Lassman et al., 2017). This data increases the sample of county-days for which we have both $PM_{2.5}$ and ozone measurements, and allows us to estimate a 2-pollutant model, to test for lagged effects of pollution exposure on aggressive behavior, and to estimate dose response functions.[3]

We have several important findings. First, we find that a 10% increase in same-day exposure to $PM_{2.5}$ is associated with a 0.14% increase in violent crimes, nearly all of which is driven by increases in assaults, which are indicative of aggressive behavior. Similarly, we find that a 10% increase in same-day exposure to ozone is associated with a 0.3% increase in violent crime or a 0.35% increase in assaults. In contrast, we find that changes in $PM_{2.5}$ or ozone have no statistically significant effect on any other category of crime. The results are robust to a battery of tests and alternative specifications, and are not explained by weather phenomenon such as heat waves or precipitation. Second, we show that daily lags of pollution do not qualitatively affect criminal activity indicating the effects are not cumulative and are in fact contemporaneous. Third, we show that the effects of $PM_{2.5}$ are largest at lower temperatures while the effects of ozone are largest at relatively higher temperatures. Finally, we estimate dose response functions and show that the $PM_{2.5}$ effects are increasing until 20 $\mu g/m^3$, but level off shortly thereafter. In contrast, the dose response function for ozone demonstrates an inverted U shape, indicating the effects begin to decline at higher ozone concentrations.

Our results have important implications for future research and policy. Air pollution is a substantial global issue. In 2015, ambient air pollution was considered the fifth ranking mortality risk factor with exposure to $PM_{2.5}$ estimated to have caused 4.2 million deaths (Cohen et al., 2017). Likewise, communities and individuals that are exposed to high levels of pollution incur higher health care costs, lower labor productivity (Adhvaryu et al., 2014; Borgschulte et al., 2018; Chang et al., 2016; 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 results indicate there are important but understudied effects of pollution beyond long-term health effects and the extent of our understanding of the social costs of pollution may be limited by the current scope of research. For instance, our results suggest that a policy that reduces daily $PM_{2.5}$ or ozone across the US by only 10% will save \$405 million -\$1 billion in crime costs per year via reduced assaults.

The remainder of the paper proceeds as follows. The following section places our paper within a large group of relevant literature and discusses plausible mechanisms driving our results. We then outline the data used in the paper and provides summary statistics and descriptions of the data cleaning process. Section 4 presents our econometric model and describes the identification assumptions. Section 5 presents our results, Section 6 provides a discussion, and Section 7 concludes.

2. Literature review

The mechanisms linking short-term pollution exposure to aggressive behavior are not well understood. 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). Some of the components of PM can be directly toxic or 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 et al., 1999; Zahran et al., 2017). While there is some experimental evidence that short-term pollution exposure (PM and ozone) can promote aggressive behavior via increased anxiety (Lu et al., 2018), we cannot directly identify the physiological pathways driving our results. However, our findings are consistent with previous research and suggestive that pollution is a contemporaneous irritant that may spur impulsive aggressive behavior (Bondy et al., 2018; Herrnstadt et al., 2016; Lu et al., 2018; Zou, 2018).

[1] There are three other unpublished manuscripts in the economics literature that also attempt to identify this relationship (Bondy et al., 2018; Herrnstadt et al., 2016; Zou, 2018).

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

[3] In the Appendix we show the results are similar when using the raw EPA monitor data.

Our research also relates to the literature on the factors that influence criminal behavior more broadly, and the costs such behavior imposes on society (Anderson, 1999; Bishop and Murphy, 2011). For instance, Becker (1968) suggested that the frequency of criminal activity is directly related to the probability of arrest. More recently, Card and Dahl (2011) document the effect of unexpected losses in Sunday night football on domestic violence. Similarly, Doleac and Sanders (2015) find that decreasing daylight increases crime. James and Smith (2017) and Komarek (2018) find that oil and gas development influences crime. A large body of evidence suggests that weather, and particularly heat, increases criminal activity (Blakeslee and Fishman, 2018; Field, 1992; Jacob et al., 2007; Mapou et al., 2017; Ranson, 2014). Yet, the influence of air pollution on crime has received little attention.

The one published study we are aware of, Lu et al. (2018), combines annual crime data with annual pollution measures for six major pollutants spanning 97% of the US population. Lu et al. (2018) find that cities with heavier air pollution tend to also have higher criminal activity. The authors run three additional experiments to further understand the mechanism behind this result and find that increased pollution exposure is associated with increased anxiety, which they argue could affect morality.

Three working papers in the economics literature also explore the relationship between pollution exposure and crime. Herrnstadt et al. (2016), finds evidence that short-term increases in air pollution increase crime in Chicago and Los Angeles. The authors exploit wind patterns relative to known air pollution sources to estimate the impact of pollution on crime.[4] 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 and they instrument pollution with wind direction as a robustness check. While wind direction is likely uncorrelated with daily crime, in their preferred instrumental variables model, the first stage F-statistic is fairly small indicating that wind direction is not the strongest of instruments for daily air pollution. Finally, Zou (2018) exploits an EPA policy in which pollution is monitored only once every six days to determine if firms are avoiding polluting on monitoring days. Zou (2018) finds that pollution is 1.6% lower on monitored days and this decrease is associated with lower crime.

Our study differs from and is a compliment to Herrnstadt et al. (2016), Lu et al. (2018), Bondy et al. (2018), and Zou (2018) in three important ways. First, we construct a daily, county-level dataset of pollution and crime spanning a sample of the entire continental US including both urban and rural populations. Second, we exploit several unique properties of our data to estimate dose response functions, to look for avoidance behavior via in-home versus out-of-home crime, and to determine whether the effects are mitigated or enhanced by wildfire smoke and temperature. Third, we find remarkably similar effects to those of Herrnstadt et al. (2016), Bondy et al. (2018), and Zou (2018); and together, our studies provide compelling evidence of a novel impact of pollution.

3. Data

We merge data on crime, pollution, wildfire smoke, and weather to produce a dataset that spans the continental United States from 2006 to 2013. The United States Federal Bureau of Investigation (FBI) maintains a crime database known as the National Incident Based Reporting System (NIBRS) (UCR, 2004). The NIBRS provides incident-level crimes by category at the county-day level based on reports by approximately 18,000 city, university and college, county, state, tribal, and federal law enforcement agencies. Unfortunately, daily reporting is not required by the FBI and therefore not all states report crimes at the daily level. Fig. 1 shows the distribution of the 397 counties for which we have data.

Crimes are recorded based on the offense reported to the law enforcement agency and not whether an individual was prosecuted for a crime. While laws differ across jurisdictions, the NIBRS requests that reporting agencies comply with a common set of crime definitions. The NIBRS reports 51 different categories of crime, which we aggregate into two major categories: violent crime and property crime. We also explore the relationship between pollution and several subcategories of violent crime including assault and several subcategories of non-violent property crime including theft and other. Table 1 contains the mapping of all individual categories into our constructed aggregate categories. If multiple crimes are reported during the same incident, the NIBRS records the most significant offense based on a hierarchy.[5]

We use surface-level $PM_{2.5}$ and ozone concentrations as measures of air pollution. The Environmental Protection Agency (EPA) maintains the Air Quality System (AQS) network of monitors that measure ozone, $PM_{2.5}$ and other pollutants.[6] We use the daily mean ozone measurements per county as our primary measure of ozone. However, not all monitors in the AQS report daily measurements and not all counties have pollution monitors. To address these spatial and temporal gaps in the data, we estimate $PM_{2.5}$ concentrations between monitors using ordinary kriging, a geostatistical interpolation method. This process provides $PM_{2.5}$ data for every ozone monitor location and every ozone monitored day in the data. 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; Berman et al., 2015). An ordinary kriging approach may be preferred in the absence of land use or environmental covariates that can

[4] 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., 2013a).

[5] The NIBRS hierarchy is (from most significant to least) criminal homicide, forcible rape, robbery, aggravated assault, burglary, larceny (except motor vehicle theft), motor vehicle theft, and arson (UCR, 2004).

[6] Data can be downloaded from https://aqs.epa.gov/aqsweb/airdata/download_files.html.

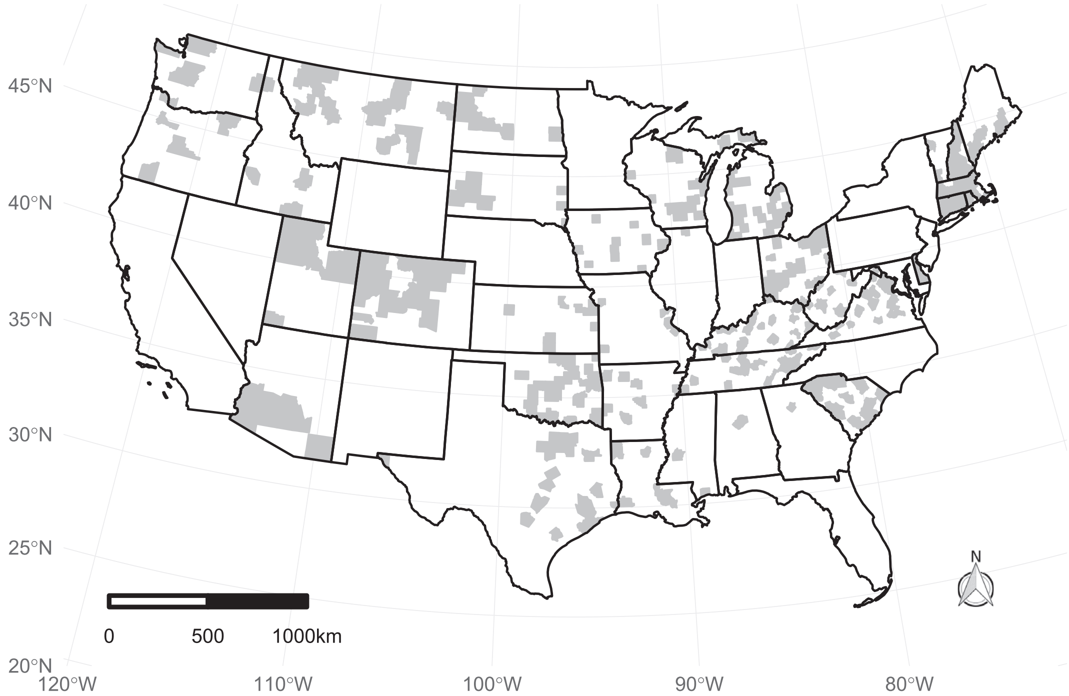

Fig. 1. This figures displays the counties in our sample. N = 397.

Table 1
Categories of crime.

Aggregate Category	Crimes Included
Violent	Aggravated Assault, Simple Assault, Forcible Fondling, Forcible Rape, Forcible Sodomy, Justifiable Homicide, Kidnappings/Abduction, Murder, Non-negligent Manslaughter, Negligent Manslaughter, Rape, Robbery, Sexual Assault with and Object, Sexual Assault, Sodomy, Statutory Rape
Assault	Aggravated Assault, Simple Assault
Robbery	Robbery
Property	All Other Larceny, Burglary/Breaking and Entering, Credit Card/Automatic Teller Theft, Destruction/Damage of Property, Motor Vehicle Theft, Pocket-Picking, Purse-snatching, Shoplifting, Stolen Property Offenses, Theft From Building, Theft from Coin-Operated Vending Machines, Theft From Motor Vehicles, Theft of Motor Vehicle Parts
Vehicle Theft	Motor Vehicle Theft, Theft From Motor Vehicles

be incorporated to improve interpolations.[7] 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.[8] We calculate the daily county-level $PM_{2.5}$ concentration as the population-weighted average of all grid points within the boundary of a county on each day in the sample.[9] In Appendix D, we show that the results are nearly identical when using the raw $PM_{2.5}$ monitor data from the EPA. Thus, the results are not sensitive to the kriged $PM_{2.5}$ measures.

Our third data source provides information on wildfire smoke plumes. The National Oceanic and Atmospheric Administration Hazard Mapping System (HMS) produces nationwide daily estimates of smoke plumes based on satellite imagery (HMS, 2018; Rolph et al., 2009; Ruminski et al., 2006). Smoke plumes are defined by trained analysts that monitor and review several

[7] It has been demonstrated that universal kriging or other predictive models that incorporate land use or satellite based covariates will 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). However, these models are complex and require data inputs that are not readily available at the daily scale. Additionally, our model relies on county-level crime data, so a spatial prediction surface that captures fine small-distance heterogeneity will have less utility for a county-level exposure estimate.

[8] 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.

[9] We use 15 km gridded 2015 population density data from Center For International Earth Science Information Network-CIESIN-Columbia University (2017) as the population weights when calculating the county-level $PM_{2.5}$ concentrations.

Table 2
Summary statistics.

Variable	Mean	Std. Dev.	Min.	Max.	N
Violent Crimes	7.302	13.588	0	197	542,779
Violent In-Home	4.102	7.542	0	137	542,779
Violent Out-of-Home	3.2	6.485	0	107	542,779
Assault	6.033	10.961	0	168	542,779
Assault In-Home	3.593	6.72	0	119	542,779
Assault Out-of-Home	2.44	4.653	0	82	542,779
Robbery	0.679	2.147	0	50	542,779
Property	16.704	27.421	0	334	542,779
Vehicle Theft	4.614	9.561	0	143	542,779
$PM_{2.5}$ (μg/m^3)	9.956	5.703	0.005	191.662	542,779
Ozone (ppm)	0.031	0.011	0.002	0.101	542,779
HMS	0.094	0.288	0	1	542,779
Own-adjusted HMS	0.015	0.122	0	1	542,779
Daily Max Temperature (C)	21.536	9.856	−24.54	47.24	542,779
Daily Min Temperature (C)	9.391	9.315	−36.67	31.79	542,779
Precipitation (mm)	2.972	7.805	0	251.06	542,779

Notes: All crimes reported as counts per county per day. HMS variables are dummy variables and therefore the means indicate that 9.4% of the observations in the sample are covered by a smoke plume using the raw HMS variable, for example.

automated smoke-plume detection algorithms. The spatial data files include the polygon of the plume and are produced for North America for every day since August 5, 2005. We create a gridded surface from the smoke polygons and assign a value of 1 if the grid box was under a smoke plume for any portion of the day and 0 if it was not. Further information on the smoke plume coverage and data cleaning process are provided in Appendix C.

Lastly, we collect weather data from PRISM, developed by the Oregon State University Climate Group.[10] Specifically, we extract gridded data on daily maximum temperatures (Celsius), daily minimum temperatures (Celsius), and daily precipitation (millimeters) at a 4 km spatial resolution across the entire continental US. We calculate the daily county-level weather variables as the average of all grid cells within a county on each day in the dataset. We merge the weather data to the crime, pollution, and smoke data by county and date.

3.1. Summary statistics

The combined dataset spans a sample of 397 counties in the continental US from 2006 to 2013. For reference, the population of the average county in our sample is 321,271. The smallest county has a population of 1090 (Daggett, Utah) while the largest county has a population of 4,253,700 (Harris, Texas). Seventy-three percent of the counties in our sample are considered urban by the Center for Disease Control. In total, our sample covers approximately 92 million people, or 28.3% of the US population and 11.8 million property crimes and 5.1 million violent crimes. Fig. 1 displays the locations of the counties in our sample.

Table 2 displays summary statistics for each of the variables used in estimation. Crimes are presented in daily counts; for example, the average number of violent crimes per day is 7.302 while the maximum is 197, which was in Wayne County, Michigan in January 2006. Eighty-three percent of violent crimes are assaults on average. We also observe whether the crime occurred in or out of home. For example, 56% of violent crimes and 60% of assaults occur within the home. There are 14.932 property crimes per day on average in our sample, 50% of which are thefts. The average daily maximum and minimum temperatures are 21.536 and 9.391 °C, respectively. The average daily precipitation is 2.97 mm.

The daily average $PM_{2.5}$ level is 9.96 μg/m^3 with a minimum of 0.005 μg/m^3 and a maximum of 192 μg/m^3. The minimum occurred in Benzie County, Michigan in August 2008 while the maximum occurred in Ravalli County, Montana in September 2012. In 2012, Montana experienced its worst fire season since 1910 (until 2017) with over 1.1 million acres burned.[11] The average daily mean ozone level is 0.031 ppm with a minimum of 0.002 ppm and a maximum of 0.101 ppm. Finally, we report summary statistics for the HMS smoke plume variable used in our sample. The average of the own-county adjusted HMS variable is 1.5% indicating that 1.5% of our sample is covered by a smoke plume.[12]

4. Model and identification

We estimate the following model to identify the effect of pollution on crime:

$$crime^j_{ct} = \gamma^j_{PM} PM25_{ct} + \gamma^j_o ozone_{ct} + \mathbf{X}_{ct}\boldsymbol{\beta}^j + \phi_{ct} + \epsilon^j_{ct}, \tag{1}$$

[10] http://prism.oregonstate.edu.

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

[12] See Appendix C for further details.

where $crime^j_{ct}$ is the crime count of crime type j in county c on day t (an observation is a county-day), $PM25_{ct}$ is $PM_{2.5}$ in μg/m^3 in county c on day t, $ozone_{ct}$ is the daily mean ozone level in ppm in county c on day t, $\mathbf{X}_{ct}$ is a vector of control variables including restricted cubic splines of daily maximum temperature, daily minimum temperature, and daily precipitation, and ϕ_{ct} is a county-by-year-by-month-by-day of the week fixed effect.

As $crime^j_{ct}$ is a non-negative count variable with over-dispersion, all models are estimated using Poisson quasi-maximum likelihood (PQML), which produces consistent parameter estimates, assuming the conditional mean function is correctly specified, even when the dependent variable is over-dispersed (See Wooldridge (2010), section 18.2 for details and Moeltner et al. (2013b) for an example of implementation). In other words, the consistency of the PQML does not require assumptions about the variance of $crime^j_{ct}$ conditional on covariates. However, the PQML variance-covariance matrix is not generally robust to over-dispersion or error clustering. For correct inference, we compute fully cluster-robust standard errors that are adjusted for over-dispersion and correlation in errors within counties (Wooldridge, 2010).

To be sure, we provide results from alternative modeling approaches including ordinary least squares, negative binomial, and PQML without fully robust standard errors in Appendix Table A.6. The negative binomial estimates are virtually indistinguishable from our preferred PQML estimates, and the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are not meaningfully different across models. When the PQML standard errors are not corrected for over-dispersion, the standard errors are smaller as would be expected if over-dispersion is present. Given these results, our preferred specification is the fully robust PQML model with standard errors clustered at the county level.[13]

Pollution and crime rates may have common correlations with location and time-varying unobservables. For example, $PM_{2.5}$ or ozone levels and crime rates may be correlated with county-level covariates such as traffic density, population density, demographics, and industrial activity. Failing to control for such covariates will lead to biased estimates of γ_{PM} and γ_o.

Our identification strategy explicitly addresses omitted variable bias in several ways. First, we show that endogeneity with respect to violent crimes and pollution can be addressed by including a series of high-dimensional fixed effects. In our primary specification, we include county-by-year-by-month-by-day of the week fixed effects to control for county level unobservables that are either constant over time, such as state and county-level policies, or that are time-variant, such as changes in population density, demographic composition, seasonal variation in pollution or crime, or changes in state and county-level policies that limit pollution or crime enforcement. These fixed effects also control for cyclical within-week, within-county variation in pollution and crime. Thus, our data allows us to compare for example, the effect of changes in pollution within a series of Mondays within a given county within a given month. We argue that changes in pollution across a series of Mondays within a county-month, conditional on weather controls, is random and thus exogenous to crime.

Second, crime has been shown to respond to changes in temperature, and temperature is generally correlated with air pollution (Field, 1992; Jacob et al., 2007; Ranson, 2014). Thus, failure to adequately control for temperature, and weather more generally, will lead to biased estimates. To address this concern, we include temperature and precipitation splines in our primary specification, we provide robustness checks with alternative functions of temperature, and in Section 5.3 we perform a series of tests to show that our results are not confounded by unaccounted for variation between temperature and air pollution. For example, we show that effect of $PM_{2.5}$ on violent crime is larger at lower temperatures, opposite of the effect of temperature alone.

5. Results

We first present a series of specifications to demonstrate the strength and consistency of our primary model using violent crimes as the dependent variable. Next, we compare the coefficient estimates in violent crime models to non-violent crime models. We then explore the potential mechanisms behind our primary results by disaggregating violent crimes, estimating a lagged model, interacting pollution with temperature and an indicator for the presence of a wildfire smoke plume, and estimating dose response functions. Lastly, we present several robustness checks.

5.1. Primary results

Table 3 displays the results of estimating Equation (1) with violent crimes as the outcome and using various sets of fixed effects. The model presented in column 1 includes year-by-month, state, and day of the week fixed effects. The model presented in column 2 includes year-by-month, county, and day of the week fixed effects. The model presented in column 3 includes county-by-year-by-month and day of the week fixed effects while the model presented in column 4, our preferred specification, includes county-by-year-by-month-by-day of the week fixed effects. If air pollution, either $PM_{2.5}$ or ozone, and crime rates are positively correlated with omitted unobservables, then the coefficient estimates should decline from column 1 to column 4.[14] Indeed, the coefficient estimate on $PM_{2.5}$ declines substantially between columns 1 and 2 due to the inclusion of a county fixed effect, and continues to modestly decline between columns 2 and 4. Importantly, the coefficient estimates on both $PM_{2.5}$

[13] Serial correlation is a potential concern. We also run models with standard errors clustered at the month level, which actually decreases the standard errors. Therefore, clustering at the county level is more conservative.

[14] Examples of these unobservables include changes to county specific policies that might simultaneously affect crime rates and pollution. In contrast, income might be negatively correlated with pollution and crime.

Table 3
Primary violent crime results.

	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	0.0110***	0.0018***	0.0015***	0.0014***	0.0016***	
	(0.0026)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	
Ozone	−16.5899***	0.9576***	0.9271***	0.9752***		1.1278***
	(3.8405)	(0.1922)	(0.1166)	(0.1102)		(0.1167)
state FE	Y					
county FE		Y				
year-month FE	Y	Y				
county-year-month FE			Y			
dow FE	Y	Y	Y			
county-year-month-dow FE				Y	Y	Y
N	542,779	542,779	542,779	542,779	542,779	542,779

Notes: The dependent variable is violent crimes in each specification. All regressions include restricted cubic splines of daily maximum temperature, daily minimum temperature, and daily precipitation. Standard errors clustered at the county level. ***denotes significance at 1% level, **at 5% level, *at 10% level.

Table 4
Other crimes.

	(1) Assault	(2) Robbery	(3) Property	(4) Vehicle Theft
$PM_{2.5}$	0.0015***	0.0005	0.0000	0.0001
	(0.0001)	(0.0003)	(0.0001)	(0.0002)
Ozone	1.1456***	−0.0064*	0.0559	−0.0294
	(0.1091)	(0.0033)	(0.1025)	(0.1584)
county-year-month-dow FE	Y	Y	Y	Y
N	534,537	403,436	520,919	471,176

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

and ozone remain relatively stable after the inclusion of some form of a county fixed effect (columns 2–4), indicating that the majority of the endogeneity in air pollution is controlled for by the county fixed effect.[15]

Columns 5 and 6 of Table 3 present single pollutant models. The coefficient on $PM_{2.5}$ is not qualitatively sensitive to the exclusion of mean ozone from the model. However, the coefficient on mean ozone displays a slight increase when $PM_{2.5}$ is omitted. The two pollutants are not highly correlated ($corr(PM_{2.5}, ozone) = 0.15$), yet both appear to have an effect on violent crime. Thus, our preferred specification is column 4, which includes both pollutants. It is important to note that this model provides estimates of an average marginal effect with the important caveat that nonlinearities do exist in the relationship between pollutants and crime. To better understand the nonlinearities, in the following section we estimate a cubic spline of pollutants and display the results using dose response functions.[16]

5.2. Further results

Our primary estimates suggest that daily increases in $PM_{2.5}$ and ozone have a positive effect on aggregate violent crimes. In the following section we investigate the effect of changes in $PM_{2.5}$ on other categories of crime and explore the mechanisms driving our results.

Table 4 displays the results of estimating our primary model (column 4 of Table 3) using assaults, robberies, property crimes, and vehicle thefts as dependent variables. The two most common violent crimes are assaults and robberies. Columns 1 and 2 show that the violent crime effect is driven entirely by assaults, which are indicative of short-term impulsive behavior. We do find a relationship between increases in ozone exposure and robberies, but the effect is small, negative, and only marginally statistically significant. Columns 3 and 4 show that changes in $PM_{2.5}$ do not statistically significantly affect property crimes or vehicle thefts, which are a subset of property crime. These results provide national corroboration of the results reported in Herrnstadt et al. (2016).

[15] One might be concerned that rural areas have more zero crime counts that urban areas. There are 98,863 county-days in which violent crime is equal to zero in the sample. This is roughly 18% of our sample. Interestingly, there are 39,818 zeros in rural areas and 59,045 zeros in urban areas. To test if urban and rural areas are behaving differently in the data, we ran our primary model on urban areas only and rural areas only. We find that the coefficient on PM2.5 in rural areas is 0.002 with a standard error of 0.0006, while the coefficient on ozone in rural areas is −0.0149 with a standard error of 0.517. The coefficient on PM2.5 in urban areas is 0.0014 with a standard error of 0.0001 and the coefficient on ozone in urban areas is 1.01 with a standard error of 0.1103. This suggests that the effect of PM2.5 is present in both urban and rural areas, while the effect of ozone is largely present only in urban areas.

[16] To more directly compare model fit, the AIC and BIC in the violent crime linear model are 1417676 and 1417810 respectively and in the spline specification 1417562 and 1417719, respectively. While these measures weakly suggest the cubic splines provide a better fit to the data, the differences are not so large as to suggest the linear model is uninformative.

Table 5
In/out of the home.

	(1) In Home Violent	(2) Out of Home Violent	(3) In Home Assault	(4) Out of Home Assault
$PM_{2.5}$	0.0011***	0.0018***	0.0010***	0.0022***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Ozone	1.1966***	0.7116***	1.1727***	1.1225***
	(0.1057)	(0.1777)	(0.1165)	(0.1793)
county-year-month-dow FE	Y	Y	Y	Y
N	514,789	478,229	503,785	464,535

Notes: The dependent variable in column 1 is in-home violent crimes. The dependent variable in column 2 is out-of-home violent crimes. Standard errors clustered at the county level. ***denotes significance at 1% level, **at 5% level, *at 10% level.

Table 6
Daily lags.

	(1) Violent	(2) Assault
Contemporaneous $PM_{2.5}$	0.0010***	0.0011***
	(0.0002)	(0.0003)
1 day lag of $PM_{2.5}$	0.0004***	0.0004**
	(0.0001)	(0.0002)
2 day lag of $PM_{2.5}$	0.0001	0.0001
	(0.0002)	(0.0002)
3 day lag of $PM_{2.5}$	0.0001	0.0001
	(0.0002)	(0.0002)
Contemporaneous Ozone	0.7775***	0.8993***
	(0.1764)	(0.1674)
1 day lag of Ozone	0.0717	0.0341
	(0.0588)	(0.0558)
2 day lag of Ozone	−0.1591	−0.2326*
	(0.1061)	(0.1089)
3 day lag of Ozone	−0.0897	−0.1256
	(0.1018)	(0.1035)
county-year-month-dow FE	Y	Y
N	407,857	405,558

Notes: This table presents our primary specification including three days of lags of $PM_{2.5}$ and Ozone. Standard errors clustered 8 at the county level. ***denotes significance at 1% level, **at 5% level, *at 10% level.

The NIBRS data reports information on crimes that occur in the home and crimes that occur outside of the home. While we do not directly observe exposure to air pollution inside and outside of the home, indoor air pollution levels are generally lower than outside levels due to air conditioning. If individuals spend more time in their home when air pollution levels are elevated, we expect to see increased in-home violent crimes and assaults, which may indicate an increase in domestic violence. Alternatively, if in-home air pollution is lower than outdoor air pollution, then we expect to see no effect of changes in outdoor $PM_{2.5}$ or ozone on in-home violent crimes. To test these hypotheses, we estimate our primary model on in-home and out-of-home violent crimes and assaults. The results are presented in Table 5 and indicate that the effects are present in the home and out of the home. This suggests that changes in outdoor $PM_{2.5}$ and ozone affect indoor behavior, and in particular, likely impact domestic violence.

Our previous estimates indicate crime responds contemporaneously to changes in $PM_{2.5}$ and ozone. We next test for lagged effects by including a cubic lag function of three daily lags of $PM_{2.5}$ and three daily lags of ozone in our primary model.[17] Table 6 displays the results. We find that same day changes in $PM_{2.5}$ affect crime rates and the coefficients are slightly lower than our primary specification (column 4 of Table 3). The first lag of $PM_{2.5}$ is statistically significant but the coefficient is 2/5 of the primary coefficient, which could be caused by serial correlation in pollution. In contrast, all of the ozone lags are statistically insignificant when violent crime is the outcome. The coefficients on the 2 and 3 day lags are precisely estimated zeros. The results are nearly identical when separate models are estimated with lags. Our results indicate an acute response of aggressive behavior to changes in $PM_{2.5}$ and ozone.

Next, we estimate dose response functions by first replacing $PM25_{ct}$ in Equation (1) with a restricted cubic spline of $PM_{2.5}$ with knots at the 25th, 50th, 75th, and 95th percentiles (5.62, 8.37, 12.26, and 28.47 μg/m^3 respectively) and second, replacing ozone with a restricted cubic spline of ozone with knots at the 25th, 50th, 75th, and 95th percentiles (0.023, 0.031, 0.038, 0.049 ppm respectively). The dose response functions are presented in Figs. 2 and 3 with the relative rate of violent crimes on

[17] The cubic lag function is described in the Appendix Section A.

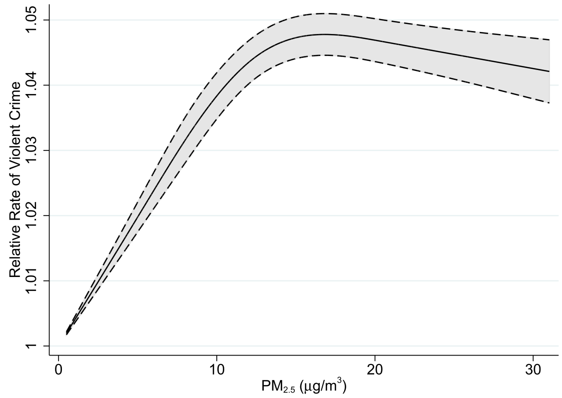

Fig. 2. $PM_{2.5}$ dose response function for violent crimes relative to 0 μg^3.

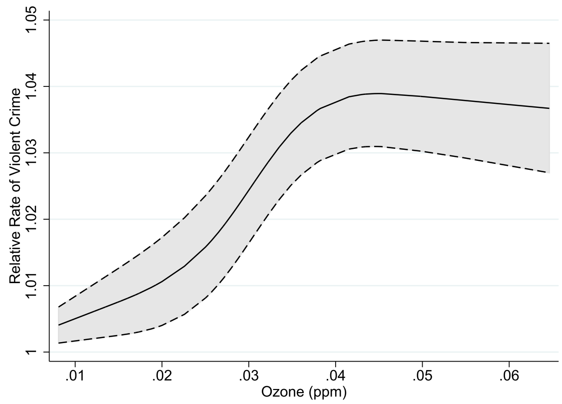

Fig. 3. Ozone dose response function for violent crimes relative to 0 ppm.

the y-axis. Estimation details are presented in Appendix B. We truncate the x-axis in Fig. 2 to $PM_{2.5}$ measures below 40 μg/m^3.[18] The standard errors above 40 μg/m^3 are quite large due to relatively few observations above 40 μg/m^3. The curve shows that the effect of $PM_{2.5}$ on violent crimes, relative to 0 μg/m^3, is sharply increasing through 20 μg/m^3 (double the $PM_{2.5}$ mean). After 20 μg/m^3, the effect remains approximately constant (the marginal effect trends toward zero). Fig. 3 shows that the relationship between ozone and violent crime is slightly different. We truncate the x-axis to values between the 1st and 99th percentiles of ozone. Again, the effect is increasing to approximately 1 standard deviation above the daily ozone mean but begins to decline shortly after.

5.3. Temperature and smoke plumes

Previous research indicates that temperature, the abundance of particulate matter, and the composition of particulate matter all affect cognitive function and behavior (Field, 1992; Jacob et al., 2007; Ranson, 2014). Correspondingly, we test whether the relationship between air pollution and violent crime is modified by either temperature or wildfire smoke plumes. Wildfire smoke exogenously increases the abundance of $PM_{2.5}$ and may increase ozone under certain environmental conditions.[19] Importantly, one might be concerned that our results are confounded by unaccounted for relationships between air pollution and temperature. Thus, this section also serves as a robustness check against this critique.

To disentangle the relationships between air pollution, temperature, and crime, we first estimate our primary specification replacing daily maximum temperature with dummy variables indicating deciles of maximum temperature to gain a sense

[18] This drops 1300 observations.

[19] Ozone forms when non-methane organic carbons and nitrogen oxide interact in the presence of sunlight (Jaffe and Wigder, 2012). These conditions often occur when organic carbons from wildfire smoke interface with emissions generated in an urban environment.

Table 7
Interactions with temperature and smoke plumes.

	(1) Violent	(2) Assault	(3) Violent	(4) Assault
$PM_{2.5}$	0.0007***	0.0007***	0.0015***	0.0017***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Ozone	0.7965***	0.8566***	0.9821***	1.1611***
	(0.1233)	(0.1335)	(0.1103)	(0.1105)
$PM_{2.5}$*1(1st Max Temp Quartile)	0.0014**	0.0016***		
	(0.0006)	(0.0006)		
$PM_{2.5}$*1(2nd Max Temp Quartile)	0.0016***	0.0019***		
	(0.0004)	(0.0004)		
$PM_{2.5}$*1(3rd Max Temp Quartile)	0.0002	0.0004		
	(0.0004)	(0.0004)		
Ozone*1(1st Max Temp Quartile)	0.3479	0.5939**		
	(0.2658)	(0.2939)		
Ozone*1(2nd Max Temp Quartile)	0.3489*	0.5252**		
	(0.2040)	(0.2433)		
Ozone*1(3rd Max Temp Quartile)	0.5047***	0.6469***		
	(0.1330)	(0.1585)		
$PM_{2.5}$*1(HMS)			−0.0009	−0.0015*
			(0.0008)	(0.0009)
Ozone*1(HMS)			0.1588	−0.0742
			(0.4854)	(0.5242)
1(HMS)			0.0063	0.0245
			(0.0300)	(0.0312)
county-year-month-dow FE	Y	Y	Y	Y
N	542,779	534,537	542,779	534,537

Notes: Columns 1 and 2 include interactions with indicators for quartiles of maximum daily temperatures. The quartiles are included in the regression in place of the restricted cubic lag of maximum daily temperature. All other controls are included including restricted cubic lags of daily minimum temperature and precipitation. In columns 3 and 4, the HMS variable is the own-county adjusted HMS variable described in Section 3. Standard errors clustered at the county level. ***denotes significance at 1% level, **at 5% level, *at 10% level.

of how temperature interacts with violent behavior. The omitted category is the fifth decile. The results are displayed in Appendix Table A.4 in Appendix D.1. The coefficients on $PM_{2.5}$ and ozone do not change substantially. Lower than median temperature deciles are associated with decreases in violent crimes and assaults while higher than median temperature deciles are associated with increases in violent crimes and assaults. The coefficients indicate that violent crime rises approximately linearly with daily maximum temperatures. These results are consistent with prior literature on the effect of temperature on crime (Field, 1992; Jacob et al., 2007; Ranson, 2014).

Second, Figs. A.1 and A.2 in Appendix D.1 display binned scatterplot relationships between daily maximum temperature and $PM_{2.5}$ and ozone respectively.[20] Fig. A.1 indicates that the relationship between $PM_{2.5}$ and temperature is quadratic and follows a U shape. Specifically, the mean daily maximum temperature in our dataset is 19 °C and is associated with the lowest average $PM_{2.5}$. Notably, temperatures above *and* below average are associated with higher $PM_{2.5}$ levels. One possible explanation for higher $PM_{2.5}$ levels at low temperatures is that certain cities, such as Salt Lake City, have severe inversion problems in the winter. Fig. A.2 on the other hand indicates that ozone increases approximately linearly with temperature.

Third, we estimate our primary model including interactions between $PM_{2.5}$ or ozone and dummy variables of daily maximum temperature quartiles. The omitted category is the 4th quartile of maximum temperature. Table 7 displays the results. We find that the effect of $PM_{2.5}$ on violent crimes and assaults is highest at lower temperatures, which stands in contrast to the finding that lower temperatures decrease violent crimes on average (Table A.4). Importantly, the relationship between violent crime and $PM_{2.5}$ remains present at higher temperatures but some of the effect is likely overshadowed by the direct effect of temperature. Together, these results provides evidence that the estimated effect of changes in $PM_{2.5}$ on violent crime is not being driven by unaccounted for correlation between weather and $PM_{2.5}$. On the other hand, the effect of ozone on violent crime and assaults is largest in the 3rd quartile of ozone, which may reflect the importance of sunlight in the ozone formation process. This finding is also consistent with the observed relationship between ozone and temperature displayed in Fig. A.2.

Finally, we interact $PM_{2.5}$ and ozone with the own-county adjusted HMS variable, described in Section 3. This variable is an indicator for whether or not a smoke plume was present above county *c* on day *t* and was significantly impacting surface-level $PM_{2.5}$.[21] The results are presented in columns 3–4 of Table 7. We find no significant indication that the effect of wildfire smoke on crime is different from the effect of general PM2.5. However, this analysis is subject to several caveats. The smoke indicator (HMS) is highly correlated with PM2.5 and the frequency of smoke days is small relative to the total number of observations. As such, a different wildfire smoke exposure metric may yield different results.

[20] These figures were generated using Stata's binscatter command.

[21] Details on the smoke plume variable can be found in the Appendix Section C.

5.4. Robustness checks

Model misspecification is a concern given the complex relationships between pollution exposure, temperature, and physiological responses. We test the robustness of our results by estimating a variety of alternative specifications including replacing the kriged $PM_{2.5}$ data with the raw EPA monitor data, alternative functional forms, and including a control function. In each of the following specifications, we focus only on violent crimes and assaults as the dependent variables.

We begin by comparing estimates using the kriged $PM_{2.5}$ to estimates using the raw pollution monitor data from the EPA.[22] The EPA does not collect $PM_{2.5}$ data from all counties and the monitors are clustered in population centers. Thus, the raw EPA monitor data could introduce selection bias. On the other hand, the kriged $PM_{2.5}$ measures provide information on $PM_{2.5}$ for all locations in the US, but introduce potential measurement error via the kriging process, which we assume is random and can be considered classical measurement error. The results are displayed in the Appendix Table A.5. Column 1 displays the results using the raw monitor data while column 2 displays our primary specification using the kriged $PM_{2.5}$ measures estimated on the sample of data used in column 1. The coefficient using the monitor data is 0.0017 while the coefficient using the kriged $PM_{2.5}$ data on the same sample is 0.0015. This indicates that the kriged $PM_{2.5}$ and the raw monitor $PM_{2.5}$ data yield similar results and the kriging process does not introduce significant additional measurement error.

To address potential concerns that our estimates are sensitive to modeling assumption, we replicate our primary results using alternative sets of fixed effects (Table A.6), using ordinary least squares (OLS) (columns 1–2 of Table A.7), and using negative binomial regression (columns 3–4 of Table A.7). The alternative fixed effects results are consistent with results presented in Table 3 in that the omission of a county fixed effect increases the coefficient estimates on $PM_{2.5}$. When adjusted for the modeling approach, the OLS estimates are nearly the same as the Poisson estimates. Likewise, the negative binomial estimates are nearly identical.

6. Discussion and mechanisms

The results suggest that changes in $PM_{2.5}$ and ozone have significant acute effects on violent crimes with a particular emphasis on assaults. Assaults include physical attacks, which is likely indicative of impulsive and aggressive behavior. In contrast, we find no relationship between $PM_{2.5}$ or ozone and non-violent property crimes. One possible explanation for these findings is that assaults and property crimes are motivated by different factors. For instance, we hypothesize that many property crimes are likely motivated by need, whereas assaults are more likely to be motivated by aggravation. A contemporaneous change in air pollution is unlikely to affect an individual's incentive to steal, but it may alter an individual's disposition via some physiological pathway.

Though our data does not allow us to directly identify the physiological pathways driving our results, we can turn to research in epidemiology and public health to shed some light on several plausible mechanisms. For example, environmental pollutants including fine particulate matter air pollution can induce biological processes, like systemic inflammation, that are associated with chronic and short-term health responses such as respiratory problems (Brook et al., 2004; Donaldson et al., 2001). In turn, short-term changes in systemic inflammation can exacerbate cognitive and motor symptoms of disease and accelerate disease progression (Cunningham et al., 2009). If similar biochemical and biological mechanisms (i.e. cellular oxidative stress and systemic inflammation) underlie aggressive behavior, transient ambient air pollution levels could be associated with an increased propensity for aggressive behavior. Moreover, other research shows that acute changes in air pollution may interact with psychological factors, including perceived control, coping resources, impulsiveness, and certain personality traits that may mediate the influence of physical environmental stressors (Lu et al., 2018; Power et al., 2015; Sass et al., 2017). Our findings suggest further research on the effects of transient air pollution exposures on cognitive and behavioral outcomes, and particularly aggressive behavior, is warranted.

Our results also have important policy implications. In particular, the dose response functions indicate that the majority of the deleterious effects of air pollution occur at levels well below the EPA National Ambient Air Quality Standards and are not due to extreme air quality days.[23] This result is consistent with findings in epidemiological literature on physical and biological health outcomes that – for numerous adverse health outcomes in children and adults – suggests that interventions to reduce $PM_{2.5}$ exposures are only anticipated if very low levels of $PM_{2.5}$ can be achieved (lower than EPA and national guidelines). Thus, police precincts and policy makers can expect increases in simple assaults even when $PM_{2.5}$ or ozone are only slightly elevated.

We can put these results into context by generating some back of the envelope estimates of the social cost of the changes in assaults. We find that a 10% increase in $PM_{2.5}$ is associated with a 0.15% increase in assaults per county per day and a 10% increase in ozone is associated with a 0.35% increase in assaults per county per day. Using the average assault count, this translates to 0.009 (95% CI = {0.008, 0.01}) more assaults per day per county from $PM_{2.5}$ and 0.021 (95% CI = {0.017, 0.025}) more assaults per day per county from ozone. Estimates of the cost of assault vary widely in the literature (Wickramasekera et al., 2015). Cohen et al. (1994) provide a detailed accounting of the cost of assault and are careful to distinguish between the direct and indirect

[22] We construct the daily county pollution measure by calculating the average of the daily reported $PM_{2.5}$ of all monitors in the county. We then apply these methods to the kriged $PM_{2.5}$ measurements that lie over the pollution monitor location.

[23] For example, the $PM_{2.5}$ Ambient Air Quality Standard is 35 $\mu g/m^3$.

costs.[24] Cohen et al. (1994) estimates the direct cost of assault to be $16,500 (in 1987 dollars) or roughly $36,000 in 2018 dollars. In contrast, McCollister et al. (2010) estimates that the total cost of an assault is $107,020 in 2018 dollars.[25] We use the total cost of $107,020 to generate an estimate of the costs of increased air pollution on aggressive behavior.

Using these values, we estimate that the costs of increased assaults from a 10% increase in $PM_{2.5}$ is $384,485 (95% CI = {$334,246, $434,725}) and from a 10% increase in ozone is $901,660 (95% CI = {$733,358, $1,069,963}) per day across all counties in our sample, or $140 million (95% CI = {$122 million, $159 million}) from $PM_{2.5}$ and $332 million (95% CI = {$268 million, $391 million}) from ozone per year across all counties in our sample. We can also use these estimates to understand the potential effects of national policies that aim to reduce pollution. For instance, a policy that reduces $PM_{2.5}$ across the entire US by only 10% will save $405 million (95% CI = {$352 million, $457 million}) in crime costs per year via reduced assaults.[26] Likewise, a policy that reduces ozone across the entire US by only 10% will save $1 billion (95% CI = {$779 million, $1.1 billion}) in crime costs per year via reduced assaults. Though these costs may be small relative to the total health costs associated with pollution, these exercises demonstrate real additional benefits of reducing pollution.

The estimates in this paper are not without limitations. Perhaps the most troubling issue with our data is its lack of geographic coverage. Notably absent from the analysis are large states like California and New York. Unfortunately, the NIBRS does not collect data from all municipalities so we are limited by those that choose to respond. However, other unpublished manuscripts find similar results using different datasets that span different geographic regions and time periods (Bondy et al., 2018; Herrnstadt et al., 2016; Lu et al., 2018; Zou, 2018). Second, future research might explore alternative methods for correcting HMS smoke plume data to generate more accurate assessments of the relationship between wildfire smoke pollutants and aggressive behavior.

7. Conclusion

This paper identifies the effect of changes in pollution on criminal activity. We have three primary data sources at the daily-county level spanning 2006–2013. First, we use $PM_{2.5}$ measures from (Lassman et al., 2017) and ozone measure from the EPA. Second, we observe a large array of daily crimes from the FBI NIBRS program. Third, we include daily temperature and precipitation data. Our identification strategy employs a series of high-dimensional fixed effects and we perform a series of tests to ensure our results are not confounded by variation in temperature or weather.

Our primary findings are that a 10% increase in $PM_{2.5}$ is associated with a 0.14% increase in violent crimes per county per day and a 10% increase in ozone is associated with a 0.3% increase in violent crimes per county per day, nearly all of which is driven by increases in assaults. Alternatively, changes in $PM_{2.5}$ or ozone have no statistically significant effects on other non-violent crimes, which indicates that an increase in $PM_{2.5}$ or ozone can act as a short-term irritant, which can increase the propensity for violent behavior. We estimate dose-response functions to show that our effect estimates are statistically significant at pollutant levels well below the EPA National Ambient Air Quality Standards daily thresholds. We find evidence that our results are robust to a plethora of tests and alternative specifications. Overall, our results suggest a positive relationship between pollution and crime, which highlights a key social cost of pollution that is currently absent from policy discussions.

Declaration of competing interest

The Authors declare no conflicts of interest and no relevant funding sources.

Appendices.

A. A note on the distributed lag model

We use a cubic distributed lag model to estimate the lagged effects in Table 6. We do this because including the lags without a transformation results in identical coefficients with alternating signs for the 1 and 2 day lags. For instance, if the 1 day lag coefficient is 0.0003, the 2 day lag coefficient is −0.0003. This is a common problem when lags are highly collinear. The cubic model assumes that the effect over time is a smooth cubic function, which we feel is a relatively benign assumption. Specifically, for a quadratic lag function, the lag coefficients can be defined as

$$\beta_s = \xi_0 + \xi_1 s + \xi_2 s^2, s = 0, 1, 2, 3 \tag{2}$$

where the variable s defines the number of lags in the model and ξ_0, ξ_1, and ξ_2 describe the lag weights. In our case, $s = 3$. The example below only displays the lags of $PM_{2.5}$ to save space but the ozone lags are the identical and also included in the model.

[24] Table 24 in Cohen et al. (1994) details the components of the total cost of assault estimate. Direct costs include medical, mental health, property, police response, emergency transport. Indirect costs include lost productivity due to injury, mental health, and any legal proceedings, as well as pain and suffering, and risk of death.

[25] This value was used by James and Smith (2017).

[26] Note, this is extrapolating to the 3007 counties in the US from the 397 used in the sample. For the extrapolation, we use the average crime rate.

Substituting into our primary model, we get,

$$crime_{ct} = \sum_{s=0}^{3} (\xi_0 + \xi_1 s + \xi_2 s^2) PM25_{ct-s} + \mathbf{X}_{ct}\boldsymbol{\beta} + \phi_{ct} + \hat{v}_{ct} + \epsilon_{ct}$$

$$= \xi_0 \sum_{s=0}^{3} PM25_{ct-s} + \xi_1 \sum_{s=0}^{3} sPM25_{ct-s} + \xi_2 \sum_{s=0}^{3} s^2 PM25_{ct-s} + \mathbf{X}_{ct}\boldsymbol{\beta} + \phi_{ct} + \epsilon_{ct}$$

or

$$crime_{ct} = \xi_0 z_t^0 + \xi_1 z_t^1 + \xi_2 z_t^2 + \mathbf{X}_{ct}\boldsymbol{\beta} + \phi_{ct} + \epsilon_{ct}$$

where

$$z_t^0 = \sum_{s=0}^{3} PM25_{ct-s},\ z_t^1 = \sum_{s=0}^{3} sPM25_{ct-s},\ z_t^3 = \sum_{s=0}^{3} s^2 PM25_{ct-s}.$$

The values of coefficients on the lagged variables can be recovered from Equation (2) and the standard errors are computed using the delta method. The model is easily extended to its cubic analog.

B. Does response function details

In this section we provide details on the estimation of the dose response function. We primarily focus on the $PM_{2.5}$ dose response function because the ozone dose response function is estimated in a similar manner. We first replicated our primary model, column 4 of Table 3, but replaced $PM_{2.5}$ with a restricted cubic spline of $PM_{2.5}$. Specifically, we estimated the following equation,

$$crime_{ct} = rs(PM25_{ct})\boldsymbol{\gamma}_{PM} + ozone_{ct}\gamma_o + \mathbf{X}_{ct}\boldsymbol{\beta} + \phi_{ct} + \epsilon_{ct}, \tag{3}$$

where all variables are defined as in Equation (1) except $rs(PM25_{ct})$ is a restricted cubic spline of $PM_{2.5}$. $\boldsymbol{\gamma}_{PM}$ is a vector of coefficients on the spline basis variables. Knots are located at the 25th, 50th, 75th, and 95th percentiles (5.62, 8.37, 12.26, and 28.47 μg/m^3 respectively). The boundary knots are defined by the minimum and maximum values of $PM_{2.5}$, which are provided in Table 2. The number of spline bases is 1 less than the number of knots because we do not include an intercept, i.e., Fig. 2 begins at zero. Violent crimes is the outcome variable for our dose response functions, however in Table A.1 we present the spline results for both violent crimes and assaults.

We use the coefficients from this model and the spline basis to create the dose response function presented in Fig. 2 as follows. Define the spline basis as the matrix B, which is a $542{,}779 \times 3$ matrix with each of the columns being one of the three spline bases. In practice we take a random sample from this matrix. For instance, column 1 in B is $PM_{2.5}$ Basis 1 in the regression output. The coefficients on B are $\boldsymbol{\gamma}$. To generate the relative risk of violent crimes (the y-axis in Fig. 2), we use the estimated coefficients of $\hat{\boldsymbol{\gamma}}$ ($\gamma_1 = 0.0033, \gamma_2 = 0.0029$, and $\gamma_3 = -0.0106$), to get the predicted values from the cubic spline by a point-wise multiplication of $RR = exp(B * \hat{\boldsymbol{\gamma}})$ where the exp is due to the Poisson regression.

We use the following equation to generate the standard errors for each of the RR values:

$$CI = exp(log(RR) + / - sqrt(diag(B * vcov * B^T)))$$

where *vcov* is the variance covariance matrix of the parameter estimates in $\hat{\gamma}$. The variance covariance matrix is provided in Table A.3 below for reference.

Readers can replicate the does response function by accessing the data and do (run) files in the online data repository of the Journal. Or, one can recreate the dose response function in Stata using the following code:

- *set obs 40%* Set the number of observations to 40 in a blank workspace
- *generate PM25 = _n* % generate a grid of PM2.5 values
- *mkspline B = PM25, nknots(4) cubic* % make restricted cubic spline using the Stata function “mkspline.” This can be replicated with any restricted cubic spline package.
- *generate RR =* exp*(0.0033∗B1 + 0.0029∗B2 − 0.0106∗B3)* % generate the RR function by multiplying the output of “mkspline” by the coefficients from the output of Equation (3)
- *twoway line RR PM25%* Plot the results

The methodology above can be replicated to create the ozone dose response function. The coefficients on the Ozone spline are 0.3140, 3.7678, and −16.0919 respectively. The Variance Covariance Matrix of the Ozone spline coefficients is:

Table A.1
Cubic splines of pollutants.

	(1) Violent	(2) Assault
$PM_{2.5}$ Basis 1	0.0039***	0.0045***
	(0.0004)	(0.0005)
$PM_{2.5}$ Basis 2	−0.0043	−0.0054
	(0.0038)	(0.0041)
$PM_{2.5}$ Basis 3	0.0023	0.0037
	(0.0073)	(0.0079)
Ozone Basis 1	0.4968	0.9210***
	(0.3413)	(0.3332)
Ozone Basis 2	2.7684***	1.9171**
	(0.7902)	(0.7888)
Ozone Basis 3	−11.6235***	−8.6777***
	(2.5598)	(2.5843)
county-year-month-dow FE	Y	Y
N	542,779	534,537

Notes: Columns 1 and 2 include cubic spline bases for $PM_{2.5}$ and ozone. Standard errors clustered at the county level. ***denotes significance at 1% level, **at 5% level, *at 10% level.

Table A.2
Variance covariance matrix of coefficients on $rs(PM25_{ct})$.

7.646e − 07	−4.389e − 06	7.896e − 06
−4.389e − 06	.0000353	−.00006672
7.896e − 06	−.00006672	.00012703

Table A.3
Variance covariance matrix of coefficients on $rs(Ozone)$.

.18461488	−.35855398	1.0895591
−.35855398	.97147155	−3.2721637
1.0895591	−3.2721637	11.652514

C. Wildfire smoke plume data details

Smoke plumes may travel hundreds or thousands of miles from the source fire producing an exogenous increase in pollutant levels around the country (Brey et al., 2018; Ruminski et al., 2006). Although smoke plumes may appear in a satellite image above a particular county, the plumes are often transported in the free troposphere and may not significantly affect surface-level air quality (Brey et al., 2018; Ford et al., 2017; Rolph et al., 2009). This introduces measurement error in the sense that smoke plumes are often poor predictors of surface level air quality. As a consequence, the pollution monitors on the ground often do not report elevated pollution levels when a smoke plume is present in the satellite image ($HMS_{ct} = 1$). We develop a method to address this measurement error, which we define as the *own-county adjusted HMS variable*. The method is outlined in the following paragraph and is used to test whether the relationship between air pollution and violent crime is affected by wildfire smoke.

To address the discrepancy between satellite observed smoke plumes and surface-level air pollution, we follow a procedure similar to one employed by Brey and Fischer (2016). We begin by estimating county-specific background $PM_{2.5}$ means (three month seasonal mean) and standard deviations on non-HMS smoke days (days in which a smoke plume is not present). We then adjust the HMS variable in county *c* in time period *t* using the $PM_{2.5}$ measure in county *c* in time period *t*. We use $PM_{2.5}$ to adjust the HMS variable because smoke plumes are composed of particulate matter. Specifically, we set the HMS variable in county *c* in time period *t* equal to zero if the $PM_{2.5}$ measurement in county *c* in time period *t* is less than 1.64 standard deviations above the county specific background mean. Thus, $PM_{2.5}$ on a particular day must be elevated above the 95th percentile of background $PM_{2.5}$, assuming a normal distribution, for the own-county adjusted HMS variable to equal one. We find that surface level $PM_{2.5}$ is within 1.64 standard deviations of the within-county background mean on 83% of the smoke plume days in our sample (HMS = 1 days). The raw HMS variable is equal to 1 on 66,080 days in our sample while the own-county adjusted HMS variable is equal to 1 on 11,520 days in our sample. This discrepancy highlights the degree to which satellite images of smoke plumes are poor predictors of surface level $PM_{2.5}$. Importantly, we also find that surface-level $PM_{2.5}$ is greater than 1.64 standard deviations above the background mean on 27,026 non-smoke plume days, or days in which the raw HMS variable is equal to zero, which indicates that the own-county adjusted HMS variable is not simply an indicator for high pollution days and is in fact an indicator for smoke plume presence at the surface-level. We aggregate the smoke plume data to the county level using the same method that was used to aggregate the $PM_{2.5}$ data, and merge it with the crime and pollution data. We use this adjusted HMS variable to determine whether wildfire smoke significantly effects the relationship between pollution and crime.

D. Appendix tables and figures

D.1. Additional temperature information

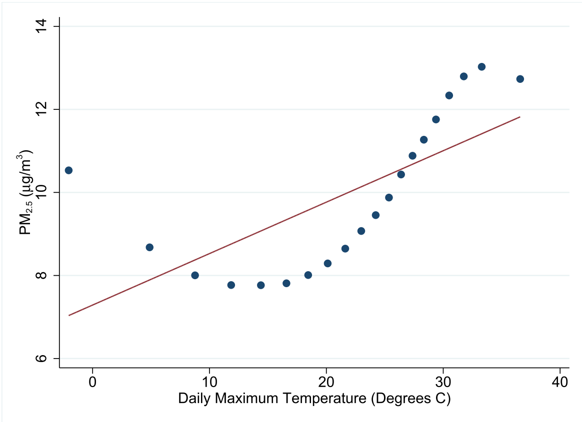

Fig. A.1 Binned Scatterplot Relationship Between $PM_{2.5}$ and Daily Maximum Temperature.

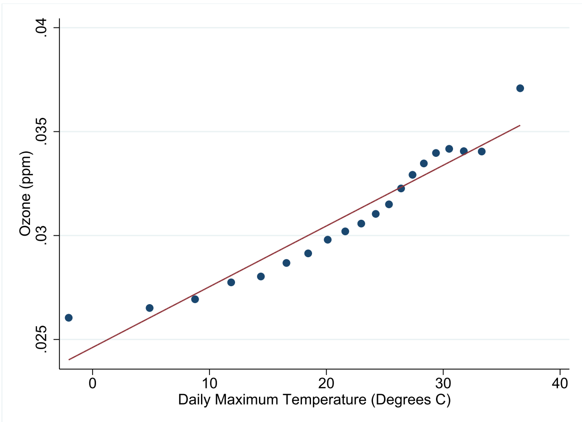

Fig. A.2 Binned Scatterplot Relationship Between Ozone and Daily Maximum Temperature.

Table A.4
Temperature deciles.

	(1) Violent	(2) Assault
$PM_{2.5}$	0.0014***	0.0015***
	(0.0001)	(0.0001)
Ozone	1.0120***	1.1956***
	(0.1061)	(0.1057)
Max Temp 1st Decile	−0.0551***	−0.0597***
	(0.0067)	(0.0067)
Max Temp 2nd Decile	−0.0343***	−0.0367***
	(0.0037)	(0.0039)
Max Temp 3rd Decile	−0.0207***	−0.0238***
	(0.0034)	(0.0036)
Max Temp 4th Decile	−0.0069**	−0.0077***
	(0.0028)	(0.0030)
Max Temp 6th Decile	0.0149***	0.0154***
	(0.0028)	(0.0032)
Max Temp 7th Decile	0.0208***	0.0244***
	(0.0033)	(0.0040)
Max Temp 8th Decile	0.0240***	0.0273***
	(0.0041)	(0.0049)
Max Temp 9th Decile	0.0301***	0.0342***
	(0.0043)	(0.0051)
Max Temp 10th Decile	0.0239***	0.0266***
	(0.0055)	(0.0062)
county-year-month-dow FE	Y	Y
N	542,779	534,537

Notes: The specifications in this table replace daily maximum temperature with deciles of within-county daily maximum temperature. The omitted category is the fifth decile. Standard errors clustered at the county level. ***denotes significance at 1% level, **at 5% level, *at 10% level.

D.2. Robustness checks

Table A.5
Monitor vs. interpolated $PM_{2.5}$.

	(1) Violent	(2) Violent
Mean Monitor $PM_{2.5}$	0.0017***	
	(0.0002)	
Kriged $PM_{2.5}$		0.0015***
		(0.0002)
Ozone	0.7213***	0.7626***
	(0.1087)	(0.1088)
county-year-month-dow FE	Y	Y
N	250,919	250,919

Notes: This table presents estimates of our primary specification using the raw $PM_{2.5}$ data from the Environmental Protection Agency (column 1). We then estimate our model with the kriged $PM_{2.5}$ data on the same sample of data (column 2). Standard errors are clustered at the county level. ***denotes significance at 1% level, **at 5% level, *at 10% level.

Table A.6
Alternative sets of fixed effects.

	(1) Violent	(2) Violent
$PM_{2.5}$	0.0107***	0.0109***
	(0.0024)	(0.0023)
Ozone	−16.2752***	−16.3247***
	(3.6863)	(3.4173)
month FE	Y	
state FE	Y	
year FE	Y	
month-year-state FE		Y
county-year-month		
dow FE	Y	Y
N	542,779	542,779

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

Table A.7
Negative binomial and OLS results.

	(1) Violent OLS	(2) Violent OLS	(3) Violent NegBinomial	(4) Violent NegBinomial	(5) Violent PQML
$PM_{2.5}$	0.0120***	0.0128***	0.0015***	0.0014***	0.0014***
	(0.0022)	(0.0023)	(0.0001)	(0.0001)	(0.0001)
Ozone	10.4822***	8.6584***	0.9482***	0.9839***	0.9752***
	(1.7345)	(1.5557)	(0.0812)	(0.0885)	(0.0805)
county-year-month FE	Y		Y		
dow FE	Y		Y		
county-year-month-dow FE		Y		Y	Y
R-squared	0.948	0.962			
N	542,779	542,779	542,779	542,779	542,779

Notes: This table presents OLS and negative binomial estimates of columns 3 and 4 of Table 3. Standard errors are clustered at the county level. ***denotes significance at 1% level, **at 5% level, *at 10% level.

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