Negative Externalities of Temporary Reductions in Cognition: Evidence from Particulate Matter Pollution and Fatal Car Crashes*

July 24, 2025

Abstract

Mounting causal evidence shows particulate matter pollution reduces real-time cognitive function and increases aggressive behavior by reducing neural connectivity through oxidative stress and neuro-inflammation. We investigate a setting in which reduced cognition can generate significant private and external costs: driving. Using exogenous variation in wind direction, we show that a one-unit increase in $PM_{2.5}$ exposure results in approximately a one-percent increase in fatal car crashes and fatalities. Further, these effects are limited to same-day pollution exposure, highlighting the immediate negative effects of high-pollution days. An across-the-board one standard deviation reduction in fine particulate matter pollution would have averted over 2,800 motor vehicle fatalities in 2019.

*We are thankful for helpful comments from Brandyn Churchill, Monica Deza, Alex Hollingsworth, Jason Huh, Cici McNamara, Andrea Monge, Matt Notowidigdo, Stephen Mead Over, Claudia Persico, Julian Reif, Nick Sanders, Thomas Thivillon, Lucy Xiaolu Wang; seminar participants at University of Texas Rio Grande Valley, The University of Alabama at Birmingham, Baylor University, TCU, Southern Methodist University, Booth Microeconomics Brown Bag; Federal Trade Commission; and conference participants at the 2023 American Society of Health Economists Annual Conference and 2024 BFI Health Economics Initiative Annual Conference.

1 Introduction and Background

Economic theory posits that when individuals are rational agents with full information and their actions only affect themselves, the decisions they make are privately and socially optimal. How bad is it for society when all three of those assumptions are violated at the same time due to the same temporary exogenous shock to cognition and decision-making capacity? We provide a partial answer to this question using a setting that millions of people find themselves in daily, in which irrational behavior, imperfect information, and negative externalities can be extremely costly (read: fatal) – driving. The temporary exogenous shock to cognition we use is random variation in fine particulate matter pollution due to changes in wind direction, a source of identifying variation that has been used to study the effect of fine particulate matter pollution on a variety of fatal health outcomes (Deryugina et al., 2019; Deryugina and Reif, 2023; Persico and Marcotte, 2022).

Good driving is cognitively demanding, particularly when accounting for complex interactions with other drivers. While basic driving tasks like staying in one's lane or following speed limits can become routine, safely navigating traffic requires sophisticated cognitive processes (e.g., anticipating other drivers' actions, maintaining spatial awareness across multiple lanes, and making split-second decisions). These activities engage brain regions responsible for reaction time, rational thought, and emotional regulation, in addition to those handling automated tasks. Recent evidence suggests that real-time decision-making and cognition is harmed by heightened particulate matter pollution (Ailshire and Crimmins, 2014; Costa et al., 2020), which implies that driving behavior could be affected as well.

Much of the previous research on the determinants of fatal motor vehicle crashes has effectively focused on the impact of reduced cognition for a subset of drivers. The bulk of this literature studies policies that affect drunk driving, such as the Minimum Legal Drinking Age (e.g., Carpenter and Dobkin, 2017; Carpenter et al., 2016), Blood Alcohol Concentration laws and associated punishments (e.g., Freeman, 2007; Hansen, 2015), restrictions on hours for alcohol sales (e.g., Green and Krehic, 2022; Lovenheim and Steefel, 2011), and ridesharing services (e.g., Burton, 2021; Dills and Mulholland, 2018). These papers generally find that policies or factors that raise the implicit cost of driving after drinking yield null to moderate reductions in alcohol-related fatal car crashes.

A smaller but related literature studies the effects of policies aimed at reducing crash risk for society's newest drivers (Deza and Litwok, 2016; Huh and Reif, 2021). When teenagers are legally allowed to drive, they are more likely to die from car crashes, and when restrictions are imposed on teenage driving (graduated driver licensing), teenagers are less likely to get arrested during hours where there is a driving curfew, implying they are driving less and getting into fewer crashes. These findings conform with brain imaging research on teenage brains and development of the prefrontal cortex, which leads to changes in cognition and self-regulation of emotion and behavior, affecting driving risks for youth (Dahl, 2008; Giedd, 2008). More directly related to our work, an environmental factor that has been shown to increase injuries and accidents, including those from fatal car crashes, is seasonal allergies (Akesaka and Shigeoka, 2023; Danagoulian and Deza, 2024). For all three populations, prior work can be considered as studying specific populations. Conditional on drivers choosing to drive under the influence (or conditional on the age or susceptibility to allergens of the driver), policies can be enacted to help mitigate negative external consequences on others caused by lower cognition levels. In our work, we show how a broad and temporary shock to cognitive ability across the whole driving population results in more fatal crashes.[1]

Our temporary exogenous shock to cognitive ability, fine particulate matter pollution ($PM_{2.5}$), has been established as harmful to brain function in both the immediate and the longer term within the medical and epidemiological literatures (Anderson et al., 2012; Cory-Slechta et al., 2023; Thangavel et al., 2022). Particulate matter pollution is a byproduct of the combustion of fuels from sources such as wildfires, power plants, and cars. The specific size

[1] In 2020, 30% of motor vehicle fatalities were due to alcohol-impaired driving (Stewart, 2022), meaning the majority of fatal crashes were not alcohol related.

of these particles are measured in microns, and the concentration is measured in micrograms per cubic meter.[2] The EPA recently lowered the limit for annual $PM_{2.5}$ concentrations from 12 to 9 $\mu g/m^3$ (Borunda, 2024), but it is not uncommon for concentrations to peak at much higher levels on a daily basis. Small particulates can travel great distances and are not necessarily confined to their area of origin as recent wildfires have shown (Burke et al., 2021; Fowlie et al., 2019; Miller et al., 2024).

Small particulates cause oxidative stress and neuro-inflammation in both humans and animals, which is believed to be a result of increased production of proinflammatory mediators and reactive oxygen (Costa et al., 2020; Hahad et al., 2020). Fine particulates are harmful to brain function because they cross the blood-brain barrier and reduce oxygen to the brain, affecting both the central nervous system and brain health. An important contributor to particulate matter is traffic-related air pollution, mostly ascribed to diesel exhaust (Costa et al., 2020). Ranft et al. (2009) show that long-term exposure to traffic-related particulate matter impairs cognitive function in the elderly and negatively affects episodic memory (Ailshire and Crimmins, 2014). Fine particulates also increase the risk of cognitive dysfunction, neurodevelopmental disorders, emotional responses such as depression, stroke, dementia, and Parkinson's disease (Hahad et al., 2020). A recent study used brain MRIs to measure changes in study participants' neural activity arising from short-term exposure to high concentrations of diesel exhaust ($PM_{2.5}$) in a lab setting (Gawryluk et al., 2023). This study found that two hours of exposure to very high concentrations of diesel exhaust (300 $\mu g/m^3$) caused reductions in neural activity in numerous regions of the brain, including areas of the brain that could reasonably be supposed to affect driving ability.[3]

The existing economics literature on the effects of pollution on mortality generally focuses on internal causes of death (Anderson, 2020; Chay and Greenstone, 2003; Deryugina

[2] 2.5 microns or 10 microns for $PM_{2.5}$ and PM_{10}, respectively

[3] Per our conversations with an M.D.-Ph.D., the parts of the brain that were activated on the MRI scans are parts of the brain that relate to spatial awareness, reaction time, rational thought, and emotional regulation.

et al., 2019; Heutel and Ruhm, 2016; Hollingsworth et al., 2021) and on external causes whose negative externalities (e.g., suicide contagion) are indirect and not as immediate as those arising from motor vehicle crashes (Molitor et al., 2023; Persico and Marcotte, 2022). Particulate matter pollution has also been linked to hampered real-time decision making and errors (Archsmith et al., 2018; Künn et al., 2019), worse educational outcomes (Komisarow and Pakhtigian, 2022; Persico and Venator, 2019; Pham and Roach, 2023), increased aggression and crime (Bondy et al., 2020; Burkhardt et al., 2019; Du, 2023; Herrnstadt et al., 2021; Jones, 2022), and documented earnings losses and a reduction in daily labor supply (Borgschulte et al., Accepted; Hoffmann and Rud, 2024).

We examine the effect of fine particulate matter exposure on fatal motor vehicle crashes. All else equal, the more drivers on the road with reduced cognition, be it from alcohol consumption, a not-yet-fully-developed prefrontal cortex, age-related cognitive decline, or environmental factors, ceteris paribus, the higher the likelihood of crashes.[4] Using the Fatality Analysis Reporting System (FARS) data on fatal motor vehicle crashes combined with daily pollution monitor data from the Environmental Protection Agency for 2005-2019, we find that a one-unit increase in predicted particulate matter exposure is associated with 1.09% more fatal crashes on any given day, relative to the mean. This effect size persists across functional form specifications, the inclusion or exclusion of control variables, and the use of a different data source to predict $PM_{2.5}$ concentrations. We also test against a randomized matching procedure as in Hsiang and Jina (2014) and conclude that our primary results are not an artifact of model-induced bias. Additionally, our results are robust to randomly dropping 5% of observed counties as Broderick et al. (2021) suggest as an additional check when the amount of observational units is large.

We also measure how traffic fatalities respond to differences in particulate matter pollution. Fatalities are an important outcome in their own right as, ultimately, from a policy

[4]A point elaborated on more fully in the context of drunk driving with a theoretical model in Levitt and Porter (2001).

perspective, we care about the number of deaths due to heightened fine particulate matter pollution. We find that a one-unit increase in mean particulate matter concentration is associated with a 1.23% increase in traffic fatalities. Put differently, a one-standard-deviation increase in $PM_{2.5}$ corresponds to a 7.8% increase in motor vehicle fatalities. The increase in fatalities is driven largely by deaths resulting from impulsive driving as opposed to those resulting from cognitive errors, but there is some evidence that deaths increase for those deemed not at fault for the crash as well. If we reduced pollution exposure by one standard deviation across the board, our estimates imply that over 2,800 motor vehicle fatalities could be avoided yearly. We quantify the effect of reducing fine particulate matter pollution by this amount to conservatively be worth $21 billion dollars per year.

Our identification strategy follows the standard instrumental variables method that many others have used, which takes advantage of exogenous changes in wind direction to determine the amount of pollution people are exposed to on a given day (e.g., Deryugina et al., 2019; Herrnstadt et al., 2021; Persico and Marcotte, 2022). Much of the variation in particulate matter exposure is due to the built environment in and around an area such as highways or electricity generation from fossil fuels. In fact, Currie et al. (2022) have shown that the Clean Air Act reduced localized pollution and is responsible for reducing racial disparities in particulate matter exposure.

There is a small but growing literature on the effects of particulate matter pollution on traffic fatalities and crashes, much of which was written concurrently and independently of this paper. Sager (2019) studies the effect of fine particulate matter pollution on fatal car crashes using temperature inversions as the exogenous determinant of pollution in the United Kingdom. We find results consistent with Sager (2019) using a different source of exogenous variation and a different context in terms of both pollution and motor vehicle crashes. Both population and average car sizes are much larger in the United States; there is a very different ‘car culture’ in the U.S., with longer commutes and suburban sprawl; and the exposure to sources of particulate matter pollution varies greatly between the two countries. In China, Shi et al. (2022) find that traffic fatalities increase by 0.64% due to a one-μg/m^3 increase in $PM_{2.5}$, and further that this effect can last for up to two days. Interestingly, Shr et al. (2023) arrive at the opposite conclusion. Using data from Taiwan these authors find that a one-μg/m^3 change is associated with a 0.59% decrease, and that this effect is not due to avoidance channels.

In the United States, Baryshnikova and Wesselbaum (2023) and Braun and Villas-Boas (2024) study the effects of pollution in New York City and California, respectively. Both find a statistically significant effect of pollution, with Baryshnikova and Wesselbaum (2023) showing that carbon monoxide and sulfur dioxide both drive aggressive behavior and accidents, and Braun and Villas-Boas (2024) showing that each μg/m^3 change is associated with a 1.3% increase in fatalities. Our results, based on data from across the United States, are very similar, providing external validity to this prior work. Hetalo (2025) studies counties in the American West and relates wildfire plumes to motor vehicle collisions. The author finds that a smoky day increases the number of deadly collisions by 7.1% compared to a day without smoke plumes. The only other study to make use of data from across the United States is Firsova (2025), who also uses daily $PM_{2.5}$ readings and data from the Fatality Analysis Reporting System as we do here.[5] The analysis presented here comes to several similar conclusions, though our paper and Firsova (2025) differ in several meaningful ways. First, our main analysis uses data from the time period after the Clean Air Act standards began in April 2005 through 2019; Firsova (2025) uses data from 1999-2013. Second, our analyses explore different sources of heterogeneity in more explicit detail. Firsova (2025) offers an interesting and robust analysis using hourly data from 2010-13, while we explore variation in accidents by measures of fault, drunk driving, pedestrian and cyclist fatalities, and age.

[5] Since the original release of the working-paper version of this paper in the latter half of 2022, our projects have unknowingly proceeded in parallel. During the peer-review process, we were made aware of this working paper.

We also explore effects on traffic stops and ticketing behavior.

We contribute to the myriad sub-fields of economics studying the effect of particulate matter exposure by getting closer to an analysis of the general-equilibrium effects of fine particulate matter pollution's cognitive harms and by more thoroughly honing in on the likely mechanism. We also contribute to the literature on determinants of fatal car crashes, with our instrument for pollution providing an exogenous shock to everybody's cognition in a localized geographic area, whereas most prior studies examine the effects of efforts to reduce drunk driving. Moreover, as climate policy is enacted to reduce emissions from both the transportation and the electric power sectors, both of which contribute to particulate matter concentrations, our research shows that the effects of wildfires, which are more prevalent and widespread in a warming world, will continue to impact cognition and driving – even after transportation and industrial sources may have reduced their particulate matter emissions.

Figure 1 shows both the spatial and temporal variation in particulate matter emissions in a bivariate map for the first year of court-ordered enforcement of the 1990 update to the Clean Air Act, 2005, and the last year of the sample, 2019. The color scale on the right-hand side of the figure is split into three equal sized partitions of the within-county annual mean concentration level for a certain year, and three equal sized partitions of the within-county standard deviation over the same year. Each column and row add up to 33.3%, and the value within each box shows how many counties belong to a specific mean-standard deviation pair. For example, the top-right corner represents the top third of counties in terms of both mean annual concentration levels *and* top third in yearly variation. This is 19.2% of counties in 2005 and 20.2% of counties in 2019. The bottom-left corner is the opposite, showing counties that have both low-variance and low-mean concentrations. Note that the threshold value determining where a partition begins is different for each of the years mapped. Indeed, one way to see how much progress has been made in reducing $PM_{2.5}$ emissions over time can be seen in the end point of average concentrations for both figures. In 2005 the highest average

$PM_{2.5}$ is 20.9 while in 2019 it is 13.2, just above the EPA's 2012 air quality standard. The within-county standard deviation also falls from a maximum of 19.4 to 11.4, though there is still a large degree of variability in particulate matter emissions with day-to-day variation that can peak at thresholds well above the EPA's guidance of 12 μg/m^3, even in 2019. These maps also show that even within states there is ample variation in both average exposure and the variability of exposure.

The remainder of the paper proceeds as follows. The next section describes the data sources and instrumental variables empirical strategy. Section 3 describes our main results and robustness checks. Section 4 concludes.

2 Data and Empirical Strategy

2.1 Data Description

2.1.1 Pollution and Weather data

Data on mean particulate matter concentrations are collected from the Environmental Protection Agency's daily summaries by monitor (Environmental Protection Agency, 2022). The number of monitors increases over time, but from 2010 onward the number of locations is consistent, with over 359,000 individual observations yearly spread over 20,000 separate sites. A limitation of using observed values from monitor-based readings is that only about 20% of counties have coverage, and daily coverage is not guaranteed for each monitor.[6,7,8]

[6]Some counties have multiple monitors while others have a single monitor. We aggregate to the county-day-level by averaging across all monitors within a county. The EPA data also includes specific coordinates for each monitor, so we are also able to construct population-weighted daily averages using the population from each census tract that a monitor is located in. These two pollution measures are nearly identical, with a correlation coefficient of 0.984.

[7]Depending on the county, the raw data consist of both continuous monitors and monitors that update approximately every three days with an FRM sampler. These two sampling methods result in statistically similar outputs. The relationship between the two monitor types can be compared using the EPA's 'PM2.5 Continuous Monitor Comparability Assessments' tool. By 2019, 81% of counties have at least one type of continual monitor.

[8]Strategic misreporting of pollution data has also been documented by Zou (2021) and Mu et al. (n.d.).

However, these monitors are located in more populated areas, which make up a majority of the observed car crash data: 56% of all fatal crashes occur within a county for which we have particulate matter readings. In a robustness check, we address the potential issue of missing data readings by using satellite-based particulate matter observations, which have no gaps in daily coverage, and our results are nearly identical.

The average daily $PM_{2.5}$ concentration is 9.78, which is just over the threshold for "moderate" air quality according to AirNow.gov's AQI Calculator (Table 1). There is substantial variation in the amount of observed particulate matter pollution within each county. On average, each county has about 99 days above the threshold level of good air quality each year with some reaching more than 250 days above the cutoff for good air quality. The within-county standard deviation is 5.86 on average with a maximum within-county standard deviation of 17.0.

We couple our particulate pollution information with wind speed and direction data from the North American Regional Reanalysis daily reanalysis data.[9] Wind conditions are reported on a 32-by-32 kilometer grid for the entire United States, which we aggregate to the county-level. From these data, we calculate the mean wind speed and wind direction, the latter of which is reported in degrees around a wind rose. For the purposes of the first stage of our IV model, we construct indicator variables dividing the prevailing wind direction into 90-degree bins. We control for wind speed in our specifications as higher wind speeds make it more difficult to maintain control of a vehicle.

Our IV strategy makes use of wind direction to predict observed particulate matter readings by location. As an illustrative example, consider a county that is located on the edge of a large body of water like a lake, river or the ocean. If the prevailing wind direction comes from the waterfront, then observed pollution will likely be low because there is no polluting activity blowing from the water. Alternatively, suppose that a neighboring county

Our IV strategy helps account for this source of measurement error.

[9]These data are collected using the climateR package by Johnson (2022).

produces particulate matter pollution through industrial activity, power generation, or high car density. When the wind blows from the direction of the polluting county we can expect higher particulate matter concentrations. These exogenous changes in wind direction allow us to address the simultaneous determination problem – more cars result in more accidents and more cars result in more particulate pollution, but we are trying to determine whether more pollution causes more accidents.

Another source of (attenuating) measurement error is that pollution monitor locations are fixed, hence they will fail to capture within-county variation in pollution, as noted in Persico and Marcotte (2022). Suppose the pollution monitor registers high air pollution one day while the rest of the county has low pollution, and the next day the pollution monitor registers low air pollution while the rest of the county has high pollution. Suppose on each day there is a fatal crash in the high pollution part of the county, so county-level crashes are the same on both days. It would then appear that pollution has no effect on crashes because variation in pollution did not correspond to variation in crashes, even though more localized measures of pollution and crashes would have picked up an effect. These offsetting sources of measurement error mean the effect of measurement error on our estimates is *a priori* uncertain. By using wind direction to predict particulate matter readings, we are limiting the variation in same-day particulate matter exposure to that which varies randomly with prevailing winds.

We also use temperature and precipitation data from the NARR reanalysis data. We control for days when the maximum temperature is below freezing to account for potentially icy conditions, and control for maximum daily temperatures that are above 85° F to account for hot days. Including an indicator for hot days is an important control as heat can also affect cognition and temperament, and may contribute to feelings of anger that could be associated with car crashes (Baylis, 2020; Colmer and Doleac, 2022).[10] We also control for

[10] In Appendix Table A.1, we present results that account for different interactions of the weather variables and potentially non-linear effects of high temperatures by controlling for more granular variations in

precipitation in deciles since precipitation affects road quality and visibility conditions.

2.1.2 FARS data

Data on fatal motor vehicle crashes and motor vehicle fatalities come from the Fatality Analysis Reporting System, which contains records of every fatal crash occurring on public roadways in the U.S. (National Highway Traffic Safety Administration, 2022). We aggregate crash and fatality data to the county-day level, and we use details about the year, month, and day of the week of the crashes. On average, there is slightly more than one crash and one fatality in a county every three days (Table 1). The FARS data contain information on crash and driver characteristics such as the blood alcohol concentration and age of the driver, and how the driver was driving at the time of the crash (e.g., speeding or failing to yield). We exploit this richness of the FARS data in a variety of robustness checks.

2.1.3 Control variables

In our main specifications we control for alcohol and marijuana policies. Data on the state's blood alcohol concentration (BAC) limit for operating a motor vehicle come from the Alcohol Policy Information System, a database maintained by the National Institute on Alcohol Abuse and Alcoholism (National Institute on Alcohol Abuse and Alcoholism, 2022). Information on the legality of recreational and medical marijuana comes from ProCon.org, a nonpartisan organization that compiles information on controversial social issues (Procon.org, 2022a,b).

2.2 Econometric Specification

We estimate both OLS and instrumental variables specifications, using Correia (2016).

temperature. We estimate a model with indicators for the maximum daily temperature of 80-85 degrees, 85-90 degrees, 90-95 degrees, 95-100 degrees, and 100+ while still including an indicator for days below freezing. Moderate days (those below 80 degrees but above freezing) are our omitted group. The estimates are robust to these alternative weather specifications.

Our preferred specification is the IV model, as the OLS estimation suffers from potential bias due to measurement error and the simultaneous determination problem, as noted above. We first estimate the following OLS equation:

$$F_{cymd} = \alpha + \beta \cdot AP_{cymd} + \mathbf{X'_{cymd}} \cdot \theta + W_{cymd} + \delta_{cmy} + \delta_{dow} + \varepsilon_{cymd} \tag{1}$$

F_{cymd} denotes the number of fatalities or fatal car crashes in county c on day d in month m and year y. AP_{cymd} is the measure of air pollution for county c on day d in month m and year y. $\mathbf{X_{cymd}}$ represents a vector of time-varying (at the daily level) control variables: the legal blood alcohol concentration limit for operating a motor vehicle, and indicators for whether medical and recreational marijuana laws have been implemented. W_{cymd} represents weather fixed effects: indicators for the maximum temperature being below freezing or above 85° F interacted with precipitation deciles and wind speed deciles. δ_{cmy} and δ_{dow} represent county-by-month-year and day-of-week fixed effects. County-by-month-year fixed effects account for demographic characteristics, the unemployment rate, and other standard county-level control variables that are measured at a monthly (or less frequent) level. Standard errors are clustered at the county level. Our primary specification weights the regression by county population, so the estimated effect is interpretable as the effect of air pollution on the average person, as opposed to the average county.[11]

Our primary sample period runs from April 2005 to December 2019. We start in April 2005, when the new Clean Air Act standards began to be enforced, so that our variation in pollution exposure primarily comes from weather events, such as wildfires (in the OLS specifications) or changes in wind direction, as opposed to pre-existing differences in air

[11] We have also considered aggregating by commuting zone to address the potential for spatial dependency in the error term arising from people driving across county borders. Commuting zones are designed to represent local labor markets, and are typically made up of several counties. We find similar-to-slightly-larger effect sizes when we use this larger aggregation, though we prefer the county specification as, in our view, the county level represents the optimal level of geography with respect to the tradeoff between more precisely capturing local pollution conditions while minimizing other sources of measurement error such as the simultaneous determination problem and spatial dependency in the error term.

pollution. We end in December 2019 so as not to coincide with the COVID-19 pandemic, which led to major changes in driving frequency, driving behaviors, cognition, and pollution.

Ordinary OLS regressions of air pollution on fatal crashes may suffer from multiple forms of bias as noted earlier. To address this concern, we instrument for air pollution levels using wind direction, which is a common instrument in the air pollution literature (Deryugina et al., 2019; Persico and Marcotte, 2022).

We estimate the following first-stage equation for the two-stage least squares regression:

$$AP_{cymd} = \alpha + \sum_{c} \sum_{b} \beta_c^b \cdot \gamma_c \cdot \mathbf{I}\{winddir_{cymd} = b\} + \mathbf{X'_{cymd}} \cdot \theta + W_{cymd} + \delta_{cmy} + \delta_{dow} + \varepsilon_{cymd} \quad (2)$$

AP_{cymd} denotes the air pollution measure for county c on day d in month m and year y. $\gamma_c \cdot \mathbf{I}\{winddir_{cymd} = b\}$ represents county fixed effects interacted with indicators for wind direction (split into 90-degree bins), with the 270-to-360-degree bin omitted. The remaining variables are the same as described above. Standard errors are clustered at the county level. The first-stage regression is weighted by the county population.

Using the predicted measure of air pollution in Equation 2, we estimate the second-stage effect of air pollution on fatal motor vehicle incidents using the following IV specification:

$$F_{cymd} = \alpha + \beta \cdot \widehat{AP}_{cymd} + \mathbf{X'_{cymd}} \cdot \theta + W_{cymd} + \delta_{cmy} + \delta_{dow} + \varepsilon_{cymd} \quad (3)$$

$\widehat{AP}_{cymd}$ is the predicted measure of air pollution from Equation 2.

3 Results

3.1 OLS

Table 2, Panel A presents our OLS results. The results in Column 1 include the county-by-month-year and day-of-week fixed effects but no other time-varying controls or weather fixed effects. A one-μg/m^3 increase in $PM_{2.5}$ is associated with a daily increase of 0.0004 fatal crashes. This effect is small and marginally statistically significant, representing a 0.12% increase. Including time-varying controls attenuates the estimate: a one-μg/m^3 increase in $PM_{2.5}$ is associated with an increase of 0.0001 fatal crashes per day, which is not significant. The effect of air pollution on motor vehicle fatalities is quantitatively and qualitatively similar to the effect on fatal crashes. In the specification with controls (Column 2), a one-μg/m^3 increase in $PM_{2.5}$ leads to an increase of 0.0003 fatalities per day, which is not significant.

3.2 Instrumental Variables

Panel B of Table 2 shows the results from our instrumental variables specification. The F-statistics for the first-stage regressions of $PM_{2.5}$ concentration on wind direction are orders of magnitude larger than the threshold for valid inference (Lee et al., 2022). A one-μg/m^3 increase in predicted $PM_{2.5}$ leads to an increase of 0.0040 fatal crashes per day. This effect is statistically significant at the 1% level and represents a 1.09% increase in the number of daily crashes. The effect size is identical when we add in weather and policy controls (Column 2, our preferred specification), although the standard errors are slightly larger: the effect is significant at the 5% level instead of the 1% level.

The results for fatalities mirror those for crashes. In the version with controls (Column 2), a one-μg/m^3 increase in predicted $PM_{2.5}$ leads to a 1.23% increase in fatalities. For context, a one-standard-deviation increase in $PM_{2.5}$ corresponds to a 7.8% increase in motor vehicle fatalities.

3.3 Robustness Checks

Our results are robust to alternative functional form specifications and all are statistically significant, as shown in Table 3. In Column 1 we estimate a linear probability model where the outcome is whether there were any crashes or fatalities on a given day. Column 2 presents results using the crash and fatality rate per 100,000 population. In Column 3, we estimate a pseudo-maximum likelihood Poisson specification. Column 4 transforms the outcome variable using the inverse hyperbolic sine. In Column 5, the OLS-IV regression results are unweighted. In Column 6, we generate our measure of predicted pollution using the CDC's modeled satellite data, which has coverage for every county-day.

We find that a one-unit increase in predicted $PM_{2.5}$ leads to a 0.23 percentage point increase in the probability of any crashes or fatalities, a 0.92% increase that is significant at the 1% level (Column 1). When expressed as a rate per 100,000 people (Column 2) we estimate a 1.19% and 1.18% increase for each outcome, respectively. All estimates for this model are statistically significant at the 1% level. When we estimate a pseudo-maximum likelihood Poisson specification, we find an increase of 0.0077 crashes and 0.0092 fatalities per day, a 2.09% and 2.33% increase relative to the mean. These effects are significant at the 1% level. Results are similar using the inverse hyperbolic sine transformation (Column 4). We present these effect sizes as marginal effects on the original scale (count of crashes or fatalities), following Norton (2022). A one-μg/m^3 increase in $PM_{2.5}$ leads to an increase of 0.0030 crashes and 0.0033 fatalities (0.83% and 0.84%), which are both significant at the 1% level. The unweighted OLS-IV regressions (Column 5) yield slightly smaller effect sizes but slightly larger (for crashes) or similar (for fatalities) percent effects relative to the weighted OLS-IV regressions. A unit increase in $PM_{2.5}$ leads to an increase of 0.0012 crashes and 0.0013 fatalities per day. These effects are statistically significant at the 1% level and correspond to a 1.23% and 1.21% increase over the mean. Lastly, we make use of satellite-based gridded atmospheric data that has been coupled with the EPA's monitor-based data to provide a more comprehensive and complete series of particulate matter data (Column 6). The advantage of using these gridded averages is that there are no missing values and wider spatial coverage; the disadvantage is that these data are available over a shorter time period (from 2001-2016).[12,13] The amount of observations increases to more than 3 million using these new data for particulate matter concentrations. In this specification, we find a statistically significant increase in both crashes and fatalities at the 5% level, and the point estimates are quite similar to our main estimates that are based on EPA monitors only. A unit increase in $PM_{2.5}$ leads to an increase of 0.0032 crashes and 0.0037 fatalities per day. These effects correspond to a 1.14% and 1.22% increase over the mean.

As a further check that we are observing the true effect of fine particulate matter pollution on crashes as opposed to a spurious correlation, we test for heterogeneous effects by the level of $PM_{2.5}$ by binning $PM_{2.5}$ concentrations. Higher levels of pollution should correspond to a larger effect on crashes and fatalities. We create indicator variables for whether the daily $PM_{2.5}$ concentration was in the upper half of the "good" range for air quality, in the moderate range, or unhealthy for sensitive groups or worse (air quality in the lower half of the "good" range is the omitted group) and re-estimate a variation of Equation 1 using these indicator variables instead of the level of $PM_{2.5}$.[14] For these regressions, we use actual $PM_{2.5}$, as opposed to our predicted $PM_{2.5}$ instrument, as predicted values are all in the "good" range, providing insufficient variation. In our sample period, the majority of high-pollution days occur due to wildfires. We exclude county-by-month-year fixed effects from this estimation because wildfires are concentrated in certain counties and months.[15] We replace them with county and month-year fixed effects, the monthly unemployment rate from the BLS (Bureau of Labor Statistics, 2022), and annual demographic variables from the Census (U.S. Census Bureau, 2022): the fraction of the population that is Black, Hispanic, other (non-white)

[12]The data are available from the CDC and make use of the EPA's 'Downscaler Model' which has information on particulate matter concentrations by census tract and by county for the entire contiguous United States (Centers for Disease Control and Prevention, 2021).

[13]To be consistent with our specifications estimated using the EPA monitor data, we start our sample for the satellite specifications in April 2005, post-Clean-Air-Act enforcement.

[14]We do not further parse the highest bin due to a lack of statistical power: less than 0.5% of the sample has a recorded air quality worse than "moderate", and less than 0.1% has a recorded air quality in the unhealthy or worse range.

[15]Large wildfires mostly occur in the late summer and fall in Western and Mountain West states.

races, male and between the ages of 15 and 24, male and other ages, and female and between the ages of 15 and 24.[16] Our results, in Table 4, confirm that higher levels of $PM_{2.5}$ correlate with more crashes and fatalities. Columns 1 and 3 reproduce Panel A and Panel B of Table 2, Column 2, respectively. Columns 2 and 4 represent Columns 1 and 3 of Table 4 with the alternate control variables, respectively. Column 5, which bins pollution levels in an OLS estimation, is equivalent to Column 2 but with pollution bins instead of levels. Note that the OLS estimate of pollution on crashes and fatalities is small (0.0005 or 0.0006) and not significant. On days where the air quality index is in the upper end of the "good" range, there are an additional 0.0043 crashes and 0.0036 fatalities relative to days where the air quality index is in the lower end of the "good" range, although this effect is not statistically significant. On days with moderate air quality, there are 0.0120 additional crashes and 0.0141 additional fatalities. These results are significant at the 5% and 10% level, respectively. On days when the air quality for $PM_{2.5}$ ranges from unhealthy for sensitive groups to hazardous, there are an additional 0.0366 crashes and 0.0376 fatalities, but these effect sizes are not statistically significant. That these estimates are less precisely estimated is unsurprising given that very few counties in the U.S. have such a high daily average level of $PM_{2.5}$. This treatment-effect heterogeneity is consistent with more air pollution having worse cognitive effects, translating into more crashes and fatalities.

We also test the hypothesis that contemporaneous same-day particulate matter concentrations are what drive our results rather than cumulative exposure. If prior days' exposure matters, then we can rule out the same-day effects that other authors have found (Archsmith et al., 2018; Persico and Marcotte, 2022). Figure 2 shows plotted coefficients from our fully-specified model with all controls while also including lags of particulate matter concentration over the prior week. The effect of prior days' concentrations cannot be distinguished from zero. These results support the notion that immediate exposure levels matter, and that the

[16] Omitted demographic categories are the fraction of the population that is white and the fraction of the population that is female and other ages.

mechanism behind our findings are increases in mistakes and higher aggression levels as prior research has shown in contexts other than driving.

As a falsification exercise, we also test whether heightened *future* levels of predicted pollution affect fatal car crashes at time t. Our results, in Appendix Figure A.1, show that future levels of pollution do not lead to increases in motor vehicle fatalities or fatal crashes. Only contemporaneous particulate matter exposure affects fatal driving outcomes.

Lastly, we run two randomized falsification exercises to strengthen our claim that variation in particulate matter is driving our result that both crashes and fatalities increase with higher pollution levels. For the first test we randomly match crashes and fatalities from one county with the particulate matter exposure and control variables from a different county. For example, in one run of the randomization exercise the crash data from San Francisco County in California may be connected with pollution, weather, and other controls from Tarrant County in Texas. We repeat this random matching exercise 200 times and estimate the model specified in Equation 3 for each random draw for both crashes and fatalities.[17] This test is able to determine if there is model-induced bias (Hsiang and Jina, 2014). That is, is it possible to recover our estimate of the effect of particulate matter exposure on crashes or fatalities when the observations of the outcome variable come from a different city? Figure 3 plots the histogram of estimated coefficients with randomized matching as well as our estimate using non-randomized data from Table 2 shown by a red vertical line. Here, it is easy to see that our estimated coefficient for the effect of pollution on car crashes and fatalities is not due to chance or model-driven bias. The mean effect size among the randomized matches is 0.00025 for crashes, and 0.0002 for fatalities, approximately 16 times smaller than the non-randomized estimate.[18] Next, we test whether some observations are overly influential in determining our main results. With hundreds of counties it is not feasible to manually check the influence of all possible small subsets of counties, so we rely on a method proposed

[17] A total of 400 random matches across both outcome variables.

[18] We also compute an average z-statistic of approximately 0.34 and 0.28 for these variables, respectively.

in Broderick et al. (2021). Broderick et al. (2021) have shown that sensitivity of estimates are due to the signal-to-noise ratio and that many results from the papers that they surveyed are not robust to dropping even only 1% of the observations. For this test, we randomly assign an identification number to each county and drop approximately 5% of the sample. We run 200 iterations of the random dropping protocol and estimate the model specified in Equation 3. Appendix Figure A.2 plots a histogram of the estimated effect size for crashes and fatalities with randomly dropped subsamples. The figure shows our estimates are not sensitive to removing observations from the sample. For crashes, we find that the mean effect size across iterations is 0.0040.[19] In fact, all of the 200 iterations are statistically significant at at least the 10% level. For fatalities, we find that the mean effect size across iterations is 0.0049.[20] These are similarly all statistically significant at the 10% level or better. We conclude from these randomization tests that our result is not due to model-induced bias, nor is it sensitive to removing particular counties.

3.4 Additional Outcomes

To get a better sense of who is most affected by fine particulate matter pollution and the mechanisms by which they are affected, we test for heterogeneous effects by measures of fault, drunk driving, pedestrian and cyclist fatalities, and age. Higher pollution can generate negative externalities with respect to car crashes in two ways: one, by drivers being cognitively affected by pollution that they did not generate and then suffering negative outcomes; two, by drivers causing crashes that negatively affect others (e.g., passengers and pedestrians). The overall increases in car crashes we find can be thought of as the former, while fatalities involving drivers not at fault, passengers, or pedestrians can be thought of as the latter. Measures of fault include impulsive behaviors such as speeding, aggressive driving, erratic driving, and passing where prohibited. They also include cognitive errors

[19] We find a mean z-statistic of 2.41.

[20] We find a mean z-statistic of 2.81.

such as distracted driving, following too closely, failure to yield the right-of-way, and driving the wrong way on the road. Additional measures of fault include overloading the vehicle, failure to comply with physical restrictions of the license, and stopping in the roadway.

Panel A of Table 5 shows the effect of higher $PM_{2.5}$ on fatalities by fault type. Column 1 shows the effect on fatalities of drivers who were at fault for any reason: a one-unit increase in $PM_{2.5}$ leads to an increase of 0.0016 fatalities, a 1.23% effect that is statistically significant at the 1% level. This effect size is largely driven by fatalities of drivers that were engaging in impulsive behaviors, although fatalities for those who made cognitive errors increase as well (Columns 2 and 3): fatalities of impulsive drivers increase by 0.0017 (2.24%) and fatalities of drivers who made cognitive errors increase by 0.0005 (0.65%); the former is statistically significant at the 5% level and the latter at the 10% level. There is also an effect of higher pollution on fatalities of those not at fault, meaning drivers who did not engage in behaviors that contributed to the crash or non-drivers: a 1.55% increase in fatalities that is marginally significant. This last result provides suggestive evidence that pollution generates negative externalities in the form of increased fatalities for crash participants who were not at fault. The increase in fatalities of impulsive drivers and, to a lesser extent, those who made cognitive errors, adds support to the notion that higher $PM_{2.5}$ affects decision-making and aggressive behavior and is likely the causal mechanism by which we see fatalities increase on high-pollution days.

Panel B of Table 5 shows the effect of higher $PM_{2.5}$ on drunk-driver-related and alcohol-related crash fatalities, where drunk-driver-related is defined as a fatality arising from a crash where at least one driver had a recorded BAC above 0.08 g/dL and alcohol-related is defined as a fatality arising from a crash where at least one driver had a recorded BAC above 0. Higher pollution has a similar effect on drunk-driver-related (Column 1) and alcohol-related (Column 2) fatalities, increasing fatalities by 0.0007 (1.92%) and 0.0008 (1.74%), respectively. However, only the effect on alcohol-related fatalities is statistically significant. As drunk-driver-related fatalities are a subset of alcohol-related fatalities, the similar effect sizes suggest that higher pollution is primarily affecting the cognition of drunk drivers, whose cognition is already impaired by alcohol. Turning to pedestrian and cyclist fatalities (Columns 3 and 4), higher pollution does not have a statistically significant effect on pedestrian fatalities or cyclist fatalities. Comparing the pattern of results, the negative externalities of higher pollution appear to be largely confined to those who are directly impacted through reduced cognition, but there is some evidence that there are negative spillover effects onto others as well.

Turning to fatalities by age, we divide the sample into six age groups: less than 16, 16 to 64, 65 and older, and then further parse the middle group into three more bins of 16 to 24, 25 to 34, and 35 to 64. Examining fatalities by age is informative for several reasons. First, a fatality of a child or young adult represents more life-years lost than a fatality of an older adult, which has implications for the social costs of pollution. Second, children cannot drive, so increases in fatalities for those under-16 are more likely to represent externalities, as they were unlikely to have caused the crash. Third, pollution may have an outsized effect on fatalities of older adults. There may be a compounding effect on cognition for older adults who also have age-related cognitive decline, making them more susceptible to the cognitive effects of pollution. Additionally, given that health declines at older ages, conditional on being in a crash, they may be more likely to die. As shown in Table 6, there is a statistically and economically meaningful increase in fatalities for prime-age adults: fatalities increase by 0.0041 for 16 to 64 year-olds (1.31%, Column 2), which is significant at the 5% level. These fatalities are split evenly across the 16 to 24, 25 to 34, and 35 to 64 age groups, although the effect for 16-to-24 year-olds is not statistically significant. The increase in fatalities among those of prime driving age represents more life-years lost than if fatalities were concentrated among the elderly (who are most vulnerable to pollution's effect on internal causes of death).

As an additional test of our mechanism by which fine particulate matter pollution leads to increased fatal crashes being worse driving, we bring in data on traffic stops (Pierson et al., 2020). We make use of county-level data on all stops made by state patrol officers. These data are collected by the Stanford Open Policing Project, and they have been processed into a standardized form that is conformable across the different reporting systems of each state patrol. Each record in the original data indicates a stop occurred, and depending on availability, we also know whether or not a warning, citation, or arrest was made for each stop. For this analysis, we focus on state-wide patrol officers because these officers are more involved with ticketing of highway drivers than a local jurisdiction that must also monitor and enforce the myriad other offenses that may occur, such as homicides or robberies. In total, we collapse millions of individual observations across 6 states that have data available for all outcome variables at the county level to daily counts.[21] Appendix Table A.2 shows estimates for outcomes across 18 states that have details on the violation type, though the additional states do not necessarily record whether a warning, citation, or arrest occurred.

Our outcome measures of interest are the total number of stops that are the most common moving violations, the number of warnings issued, the number of citations issued, the number of arrests made, and the total number of stops.[22] On an average day, approximately 173 stops are made. Of these, typically 94 stops are due to a common moving violation, 37 incidents result in a warning, and 33 stops involve a citation. Only about 5 arrests are made daily on average. The low arrest rate conforms with our expectation that state-wide patrol officers are mostly enforcing the rules of the road and are not actively investigating more serious crimes. Arrests are generally only made if someone is driving under the influence or if they are found to be in possession of contraband. We also explore how the proportion of ticketing type changes. For example, if higher pollution leads to more extreme or reckless driving, then we might expect the proportion of citations or arrests relative to all stops to

[21] These states are Arizona, California, Florida, Montana, North Carolina, and Wisconsin.

[22] The most commonly and consistently recorded moving violations across states are speeding, careless or reckless driving, any kind of stop that is related to driving under the influence of alcohol or drugs, running a red light or stop sign, failure to yield, driving the wrong way or in the wrong lane, and a collision.

increase.

Table 7 presents instrumental variables results for the fully specified model with all control variables included. Panel A shows the marginal effect of a one-μg/m^3 increase in $PM_{2.5}$ on the number of common moving violations, warnings, citations, and arrests in a day, as well as the effect on all stops, which includes stops made for reasons such as equipment or license-restriction violations (in addition to the less commonly recorded moving violations). Panel B shows the marginal effect of an increase in $PM_{2.5}$ on the ratio of each of the former dependent variables relative to all stops in a day.[23]

We find that particulate matter exposure has precisely estimated null effects on the count of common moving violations, warnings, citations, arrests, and all stops. This is true for both our sample of 6 states with all outcome type indicators, and the larger sample presented in Appendix Table A.2. While one may expect stops to increase on high-pollution days if there is worse driving behavior, the increase in fatal crashes may divert law enforcement resources to assist with the crash response and away from stopping and ticketing drivers. Additionally, officers may reduce their labor supply (stopping and ticketing drivers) on higher-pollution days due to pollution-induced physical and cognitive impairments, or due to avoidance behavior. Reductions in labor supply on high-pollution days have been documented in other labor market contexts (Hoffmann and Rud, 2024). The null effect that we find for all stops is the net effect of all these potential outcomes. In Panel B, there is suggestive evidence that citations increase while warnings decrease, but this is not statistically significant. We do see that the proportion of arrests increases slightly, and this is statistically significant at the 5% level. The effect size is somewhat muted, indicating a 0.60% increase relative to the mean, slightly lower than the effect we find for fatal crashes. However, this estimate resonates with

[23] Appendix Table A.2 expands the sample and includes 18 states with data on the specific violation that occurred. For this table we are still able to differentiate between moving violations and all violations, but indicators for whether or not a warning, citation, or arrest occurred is sporadic. Because of inconsistent data for this set of states, we do not show estimates for the proportion of each occurrence, because the inconsistencies across states may bias our results.

our finding that high-particulate-matter days result in an increase in poor decision-making, the likes of which result in an arrest.

4 Conclusions and Policy Discussion

Particulate matter pollution has been linked to numerous negative health outcomes, decreased cognitive function, increased errors in decision-making, and increased aggression and criminal activity. In this paper, we analyze how deteriorated cognition and increased aggression could affect fatal motor vehicle crashes. We find robust evidence that particulate matter pollution leads to increases in fatal crashes and fatalities, building on prior work which has mostly been at the sub-national level or focused on other countries.[24] To identify causal effects of pollution on fatal motor vehicle incidents, we make use of exogenous shifts in wind direction in an instrumental variables framework to pin down particulate matter pollution due to natural variation and not shifts in the volume of drivers. In addition to finding detrimental effects of particulate matter exposure across different modeling strategies, we are able to rule out long-run effects of exposure. Contemporaneous exposure increases both motor vehicle crashes and fatalities, but pollution exposure over the prior week does not have an effect on fatal motor vehicle incidents. Further, the effect of air pollution is nonlinear, as higher levels of $PM_{2.5}$ are associated with greater increases in crashes and fatalities. These increases in fatalities are largely concentrated among 'at-fault' drivers who are engaging in impulsive behaviors, but fatalities also increase for those not at fault in the crash and for those making cognitive errors. These results support the hypothesis that the mechanism driving our results is real-time cognitive effects of particulate matter pollution. Fatalities are concentrated among those aged 16 to 64, showing that the elderly are not the only ones vulnerable to the harms of pollution and that pollution generates many more life-years lost

[24] Sager (2019), Shi et al. (2022), Baryshnikova and Wesselbaum (2023), Shr et al. (2023), Braun and Villas-Boas (2024), Firsova (2025).

than previously believed.

One limitation of this paper is that we are unable to observe traffic volume or vehicle miles traveled. In theory, increased pollution may induce individuals to switch to driving as their form of transportation, leading to more cars on the road. If true, then a mechanism by which air pollution leads to increased traffic fatalities would be the heightened traffic volume. This alternative mechanism does not affect the internal validity of our results. Again, given the increases in at-fault fatalities, we believe the totality of the evidence supports our proposed cognitive mechanism. A second limitation is that, absent direct monitoring of drivers, we cannot say with certainty that it is the cognitive effects of pollution driving our results as opposed to the physical health effects (e.g., respiratory distress). However, as measured by mortality, the physical health effects of pollution are longer lasting than the cognitive health effects (Deryugina and Reif, 2023), and we only find an effect of pollution on contemporaneous crashes. Presumably, if physical impairments were the cause for increased fatal crashes, we would see a more lasting effect. Further, the increases in at-fault fatalities are more consistent with the cognitive effects of pollution.

Crashes and fatalities pose significant economic costs to both the people involved and the communities these crashes occur in. Currently, the EPA assumes a value of $7.4 million as the value of a statistical life, and this number takes into account the effects that pollution has in exacerbating chronic health conditions like heart and lung disease. Our results indicate that additional costs should be considered as particulate matter pollution leads to increases in external causes of death such as motor vehicle crashes. When we translate our results into fatalities per hundred thousand people, a one-μg/m^3 increase in $PM_{2.5}$ is associated with a 0.003 increase in fatalities per hundred thousand people. Put differently, an additional traffic fatality occurs with only about 66 days of higher pollution concentrations in a moderately sized city of 750,000 people.[25]

[25] The 51st through 100th largest metropolitan areas in the United States have between approximately 500,000 and 1 million people.

How do these effect sizes compare to other determinants of fatal crashes? A 1-unit, or approximately 10%, increase in $PM_{2.5}$ increases fatalities by 1.23% whereas a 10% increase in seatbelt use decreases fatalities by 1.3%, making the effect of pollution similar in magnitude (Cohen and Einav, 2003). In contrast, the effect of pollution is an order of magnitude smaller than the effect of increasing the speed limit on highways by 10 mph (18%), which is estimated to increase fatalities by 44% (van Benthem, 2015). Despite having smaller effects than policies directly related to traffic safety, increases in air pollution have economically meaningful effects on fatal motor vehicle incidents. A one-standard-deviation increase in $PM_{2.5}$ corresponds to a 7.8% increase in motor vehicle fatalities. Consequently, an across-the-board one-standard-deviation reduction in fine particulate matter pollution would have prevented over 2,800 motor vehicle fatalities in 2019. Using the EPA's value of a statistical life, the pollution abatement efforts required would yield benefits of nearly $21 billion per year on the basis of fewer motor vehicle fatalities alone, which excludes reductions in other causes of death. In February 2024, the EPA lowered $PM_{2.5}$ standards from 12 to 9 $\mu g/m^3$. Our research suggests this new standard will save lives.

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5 Tables

Table 1: Summary Statistics

	(1)
PM2.5 Concentration (μg/m^3)	9.7765
	(6.3378)
Number of Crashes	0.3688
	(0.7708)
Number of Fatalities	0.3951
	(0.8500)
Maximum Daily Temperature (Degrees F)	69.5074
	(18.9528)
Daily Precipitation (Inches)	0.1017
	(0.2906)
Blood Alcohol Concentration Limit	0.0800
	(0.0011)
Medical Marijuana Legal	0.4938
	(0.5000)
Recreational Marijuana Legal	0.0975
	(0.2966)
Unemployment Rate	0.0608
	(0.0276)
Fraction Black	0.1427
	(0.1279)
Fraction Hispanic	0.2188
	(0.1745)
Fraction Other Races	0.0965
	(0.0726)
Fraction White	0.5420
	(0.2070)
Fraction Male Other Ages	0.4192
	(0.0128)
Fraction Male 15-24	0.0709
	(0.0114)
Fraction Female 15-24	0.0684
	(0.0110)
Fraction Female Other Ages	0.4414
	(0.0145)
Observations	1,801,724

Note: Data are from the Fatality Analysis Reporting System, EPA Air Quality Data, Alcohol Policy Information System, ProCon.org, Bureau of Labor Statistics, and U.S. Census Bureau for 2005-2019. Each observation is a county day. Statistics are weighted by the county population.

Table 2: The Effect of Air Pollution on Fatal Crashes and Fatalities

	EPA $PM_{2.5}$ (1)	EPA $PM_{2.5}$ (2)
Panel A: OLS Results		
Fatal Crashes	0.0004*	0.0001
	(0.0002)	(0.0002)
Mean of Crashes	0.3688	0.3688
% Effect	0.12	0.03
N	1,801,586	1,801,586
Fatalities	0.0006**	0.0003
	(0.0003)	(0.0003)
Mean of Fatalities	0.3951	0.3951
% Effect	0.14	0.07
N	1,801,586	1,801,586
Panel B: Instrumental Variables Results		
Fatal Crashes	0.0040***	0.0040**
	(0.0014)	(0.0016)
Mean of Crashes	0.3688	0.3688
% Effect	1.09	1.09
N	1,801,586	1,801,586
Fatalities	0.0046***	0.0049**
	(0.0018)	(0.0021)
Mean of Fatalities	0.3951	0.3951
% Effect	1.17	1.23
N	1,801,586	1,801,586
County FE		
County-by-Month-Year FE	X	X
Month-Year FE		
Day-of-week FE	X	X
Weather		X
Demographics		
Alcohol/marijuana laws		X

Note: Results in Panel A from the estimation specified in Equation 1 and results in Panel B from the estimation specified in Equation 3. The column header denotes the measure of air pollution and the row header denotes the outcome variable. Each coefficient is from a separate regression. The F-statistics for the first-stage regressions are $1.28\text{x}10^{20}$ for predicted $PM_{2.5}$ under the more parsimonious specification (Panel B, Column 1), and $2.12\text{x}10^{18}$ using the fully saturated specification (Panel B, Column 2). Outcome variables are from the Fatality Analysis Reporting System and pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019. Other control variables are the BAC limit, legality of medical and recreational marijuana, and temperature dummy (below freezing and above 85 degrees Fahrenheit) by precipitation decile by wind speed decile fixed effects. There are also county-by-month-year and day-of-week fixed effects. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Robustness Checks: Functional Form Specification and CDC Modeled Satellite Data

	LPM	Rate	Pseudo-Maximum Likelihood Poisson	IHS	Not Weighted	CDC Satellite Data
	(1)	(2)	(3)	(4)	(5)	(6)
Fatal Crashes: $PM_{2.5}$	0.0023***	0.0003***	0.0077***	0.0030***	0.0012***	0.0032**
	(0.0007)	(0.0001)	(0.0020)	(0.0011)	(0.0003)	(0.0014)
Mean of Crashes	0.2500	0.0227	0.3688	0.3688	0.0990	0.2844
% Effect	0.92	1.19	2.09	0.83	1.23	1.14
N	1,801,586	1,801,586	1,115,019	1,801,586	1,801,586	3,334,786
Fatalities: $PM_{2.5}$	0.0023***	0.0003***	0.0092***	0.0033***	0.0013***	0.0037**
	(0.0007)	(0.0001)	(0.0026)	(0.0013)	(0.0004)	(0.0016)
Mean of Fatalities	0.2500	0.0244	0.3951	0.3951	0.1067	0.3060
% Effect	0.92	1.18	2.33	0.84	1.21	1.22
N	1,801,586	1,801,586	1,115,019	1,801,586	1,801,586	3,334,786
County FE						
County-by-Month-Year FE	X	X	X	X	X	X
Month-Year FE						
Day-of-week FE	X	X	X	X	X	X
Weather	X	X	X	X	X	X
Demographics						
Alcohol/marijuana laws	X	X	X	X	X	X

Note: Results from a variation of the estimation specified in Equation 3. The column header denotes the functional form specification and the row header denotes the outcome variable and measure of air pollution. Column 1 estimates a linear probability model where the outcome is whether any crashes or fatalities occur. Column 2 uses the rate per 100,000 population of crashes or fatalities. Column 3 estimates a pseudo-maximum likelihood Poisson specification using the count of crashes or fatalities. Column 4 uses an inverse hyperbolic sine transformation of the outcome variable. Column 5 presents unweighted OLS IV regression results. Column 6 presents results using modeled satellite data from the CDC for the measure of $PM_{2.5}$ in the first-stage regression. Outcome variables are from the Fatality Analysis Reporting System; pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019 (columns 1 through 4) or the Centers for Disease Control for 2005-2016 (column 5). Other control variables are the BAC limit, legality of medical and recreational marijuana, and temperature dummy (below freezing and above 85 degrees Fahrenheit) by precipitation decile by wind speed decile fixed effects. There are also county-by-month-year and day-of-week fixed effects. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Robustness Checks: Heterogeneous Effects of $PM_{2.5}$ AQI

	OLS (1)	OLS (2)	IV (3)	IV (4)	OLS (5)
Panel A: Fatal Crashes					
$PM_{2.5}$	0.0001	0.0005	0.0040**	0.0026**	
	(0.0002)	(0.0003)	(0.0016)	(0.0010)	
$PM_{2.5}$ Upper Half of Good Range					0.0043
					(0.0045)
$PM_{2.5}$ Moderate					0.0120**
					(0.0056)
$PM_{2.5}$ Unhealthy for Sensitive Groups or Worse					0.0366
					(0.0267)
Dependent Variable Mean	0.3688	0.3688	0.3688	0.3688	0.3688
% Effect	0.03	0.12	1.09	0.71	
N	1,801,586	1,801,013	1,801,586	1,801,013	1,801,013
Panel B: Fatalities					
$PM_{2.5}$	0.0003	0.0006	0.0049**	0.0030**	
	(0.0003)	(0.0004)	(0.0021)	(0.0013)	
$PM_{2.5}$ Upper Half of Good Range					0.0036
					(0.0044)
$PM_{2.5}$ Moderate					0.0141*
					(0.0074)
$PM_{2.5}$ Unhealthy for Sensitive Groups or Worse					0.0376
					(0.0232)
Dependent Variable Mean	0.3951	0.3951	0.3951	0.3951	0.3951
% Effect	0.07	0.16	1.23	0.75	
N	1,801,586	1,801,013	1,801,586	1,801,013	1,801,013
County FE		X		X	X
County-by-Month-Year FE	X		X		
Month-Year FE		X		X	X
Day-of-week FE	X	X	X	X	X
Weather	X	X	X	X	X
Demographics		X		X	X
Alcohol/marijuana laws	X	X	X	X	X

Note: Results from a variation of the estimation specified in Equations 1 and 3. The measure of pollution for Columns 1 through 4 is $\mu g/m^3$ of $PM_{2.5}$. For Column 5, $PM_{2.5}$ is binned into groups corresponding to air quality in the upper half of the "good" range, moderate air quality, and air quality that is unhealthy for sensitive groups or worse, based on $PM_{2.5}$ concentrations. The omitted group is an indicator for air quality in the lower half of the "good" range. Columns 1 and 3 correspond to Columns 1 and 2 of Table 2. Outcome variables are from the Fatality Analysis Reporting System and pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019. Demographic controls in Columns 2, 4, and 5 are the annual fraction of the population that is Black, Hispanic, other non-white races, male between the ages of 15 and 24, male other ages, and female between the ages of 15 and 24. Other control variables (all columns) are the BAC limit, legality of medical and recreational marijuana, and temperature dummy (below freezing and above 85 degrees Fahrenheit) by precipitation decile by wind speed decile fixed effects. There are also county, month-year, and day-of-week fixed effects. Columns 1 and 3 replace county and month-year fixed effects and demographic controls with county-by-month-year fixed effects. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Heterogeneous Effects of $PM_{2.5}$ on Various Types of Fatalities

	At Fault (1)	Impulsive (2)	Cognitive Error (3)	Not at Fault (4)
Panel A				
Fatalities	0.0016***	0.0017**	0.0005*	0.0022*
	(0.0006)	(0.0008)	(0.0003)	(0.0012)
Mean of Fatalities	0.1314	0.0767	0.0781	0.1411
% Effect	1.23	2.24	0.65	1.55
N	1,801,586	1,801,586	1,801,586	1,801,586
	Drunk (1)	**Alcohol-Related (2)**	**Pedestrian (3)**	**Cyclist (4)**
Panel B				
Fatalities	0.0007	0.0008**	0.0008	0.0002
	(0.0005)	(0.0004)	(0.0005)	(0.0001)
Mean of Fatalities	0.0353	0.0462	0.1039	0.0142
% Effect	1.92	1.74	0.82	1.64
N	1,801,586	1,801,586	1,801,586	1,801,586
County FE				
County-by-Month-Year FE	X	X	X	X
Month-Year FE				
Day-of-week FE	X	X	X	X
Weather		X		X
Demographics				
Alcohol/marijuana laws		X		X

Note: Results from a variation of the estimation specified in Equation 3. The column header denotes the outcome variable. Panel A, Column 1 estimates the effect of $PM_{2.5}$ on driver fatalities where the driver was at fault. Column 2 estimates the effect on driver fatalities where the driver engaged in impulsive driving behaviors. Column 3 estimates the effect on driver fatalities where the driver made a cognitive error. Column 4 estimates the effect of fatalities of drivers who were not at fault or non-drivers. Panel B, Column 1 estimates the effect of $PM_{2.5}$ on drunk-driver-related fatalities. Column 2 estimates the effect on all alcohol-related fatalities. Column 3 estimates the effect on pedestrian fatalities. Column 4 estimates the effect on cyclist fatalities. Outcome variables are from the Fatality Analysis Reporting System and pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019. Other control variables are the BAC limit, legality of medical and recreational marijuana, and temperature dummy (below freezing and above 85 degrees Fahrenheit) by precipitation decile by wind speed decile fixed effects. There are also county-by-month-year and day-of-week fixed effects. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effect on Fatalities by Age

	<16	16-64	65+	16-24	25-34	35-64
	(1)	(2)	(3)	(4)	(5)	(6)
Effect Size: $PM_{2.5}$	-0.0001	0.0041**	0.0008	0.0015	0.0012**	0.0015**
	(0.0002)	(0.0017)	(0.0006)	(0.0010)	(0.0006)	(0.0007)
Mean of Fatalities	0.0151	0.3154	0.0630	0.0803	0.0759	0.1592
% Effect	-0.68	1.31	1.20	1.82	1.61	0.92
N	1,801,586	1,801,586	1,801,586	1,801,586	1,801,586	1,801,586
County FE						
County-by-Month-Year FE	X	X	X	X	X	X
Month-Year FE						
Day-of-week FE	X	X	X	X	X	X
Weather	X	X	X	X	X	X
Demographics						
Alcohol/marijuana laws	X	X	X	X	X	X

Note: Results from a variation of the estimation specified in Equation 3. The column header denotes the effect of $PM_{2.5}$ on fatalities by age. Column 1 estimates the effect on fatalities for ages less than 16. Column 2 estimates the effect on fatalities for ages 16 to 64. Column 3 estimates the effect on fatalities for ages 65 and older. Columns 4 through 6 break down the 16-64 fatalities into 16-24, 25-34, and 35-64 age groups. Outcome variables are from the Fatality Analysis Reporting System and pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019. Other control variables are the BAC limit, legality of medical and recreational marijuana, and temperature dummy (below freezing and above 85 degrees Fahrenheit) by precipitation decile by wind speed decile fixed effects. There are also county-by-month-year and day-of-week fixed effects. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Robustness Checks: Effect on Traffic Stops

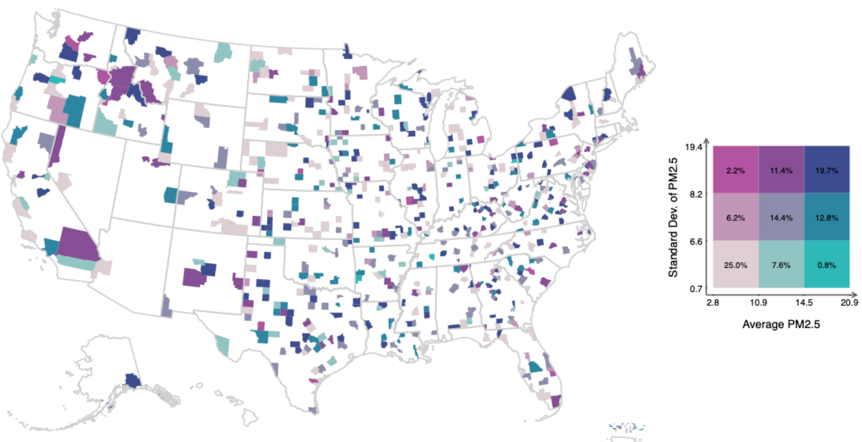
	Moving Violations (1)	Warnings (2)	Citations (3)	Arrests (4)	All Stops (5)
Panel A: Counts					
Effect Size $PM_{2.5}$	-0.8949	-0.4211	0.0773	0.0064	-1.5286
	(0.6976)	(0.3809)	(0.1388)	(0.0305)	(0.9801)
R^2	0.9588	0.9067	0.8839	0.8884	0.9668
Mean of Outcome	339.5513	115.7796	56.3267	20.1898	632.4230
% Effect	-0.26	-0.36	0.14	0.03	-0.24
N	203610	203610	203610	203610	203610
Panel B: Proportion					
Effect Size $PM_{2.5}$	0.0016	-0.0329	0.0429	0.0184**	-
	(0.0373)	(0.0384)	(0.0357)	(0.0089)	-
R^2	0.6325	0.8027	0.9562	0.8920	-
Mean of Outcome	56.6030	24.7029	23.4978	3.0589	-
% Effect	0.00	-0.13	0.18	0.60	-
N	203610	203610	203610	203610	-
County FE					
County-by-Month-Year FE	X	X	X	X	X
Month-Year FE					
Day-of-week FE	X	X	X	X	X
Weather	X	X	X	X	X
Demographics					
Alcohol/marijuana laws	X	X	X	X	X

Note: Results from a variation of the estimation specified in Equation 3. The column header denotes the traffic-stop-related outcome. Panel A shows estimates for the count of each dependent variable. Column 1 estimates the effect of $PM_{2.5}$ on all traffic stops involving the most commonly and consistently recorded moving violations: speeding, careless or reckless driving, any kind of stop that is related to driving under the influence of alcohol or drugs, running a red light or stop sign, failure to yield, driving the wrong way or in the wrong lane, and a collision. Column 2 estimates the effect on stops that result in a warning. Column 3 estimates the effect on stops that result in a citation. Column 4 estimates the effect on stops that result in an arrest. Column 5 estimates the effect on all reasons for a stop. Panel B shows estimates for each dependent variable as a ratio of outcome to all stops in percentage point units. Outcome variables are from the Stanford Open Policing Project and pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019. Other control variables are the BAC limit, legality of medical and recreational marijuana, and temperature dummy (below freezing and above 85 degrees Fahrenheit) by precipitation decile by wind speed decile fixed effects. There are also county-by-month-year and day-of-week fixed effects. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

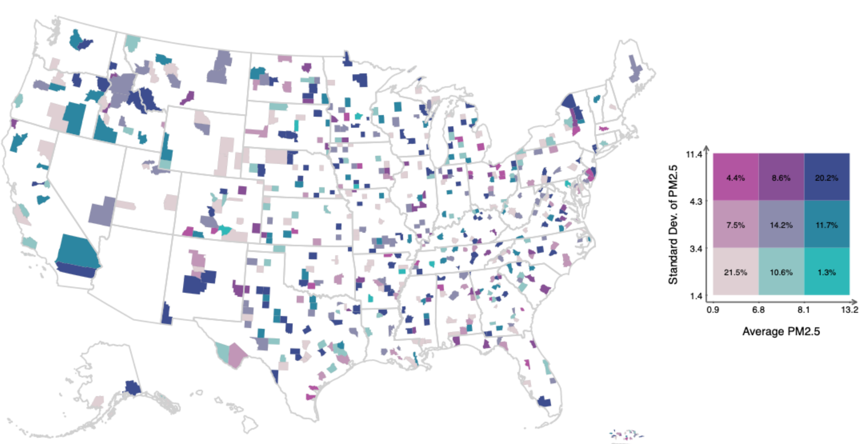
6 Figures

Figure 1: Pollution Variation Over Time and Geography

2005



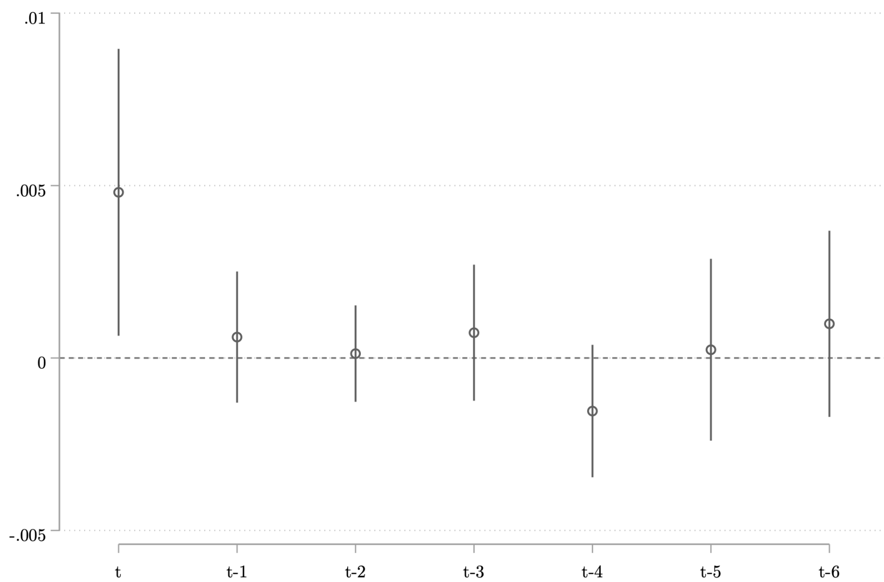
2019



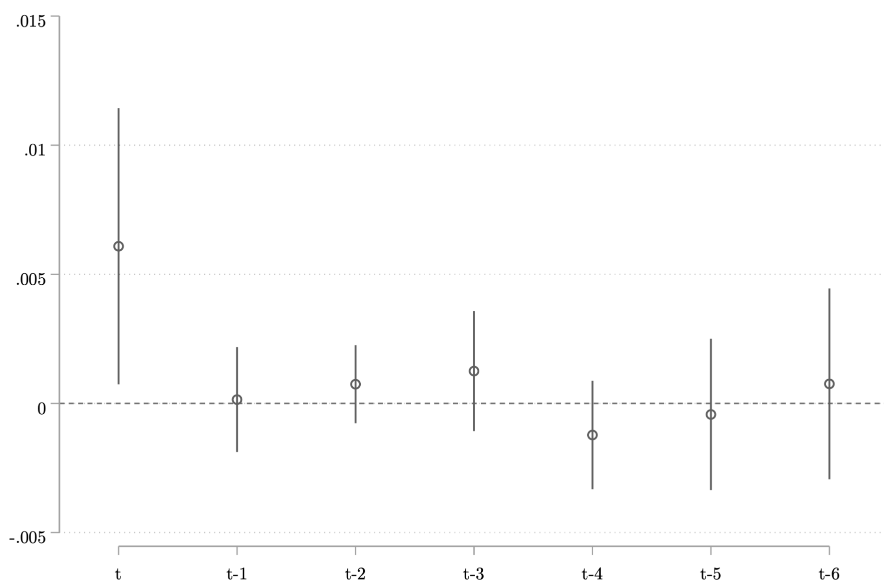
Note: Figures show within-county average annual $PM_{2.5}$ concentrations and standard deviations for two sample years, 2005 and 2019. Color scale on right-hand axis splits each variable into equal thirds (e.g. each column or row adds up to 33%). Values show the percent of counties that belong to a certain average-standard deviation pair. The top-right corner is the highest third concentration and highest third standard deviation, the bottom-left is the lowest third concentration and standard deviation.

Figure 2: Lagged Particulate Matter Exposure

Number of Fatal Crashes



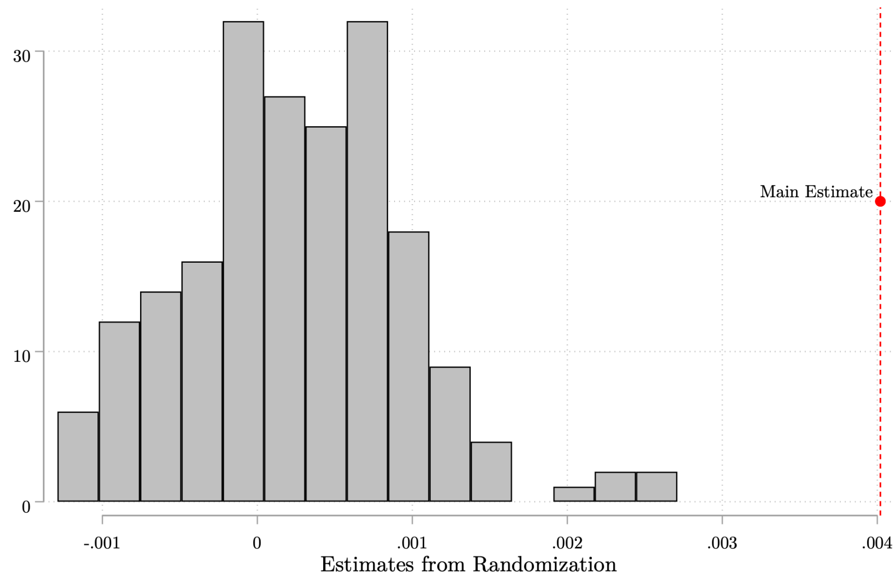
Number of Fatalities



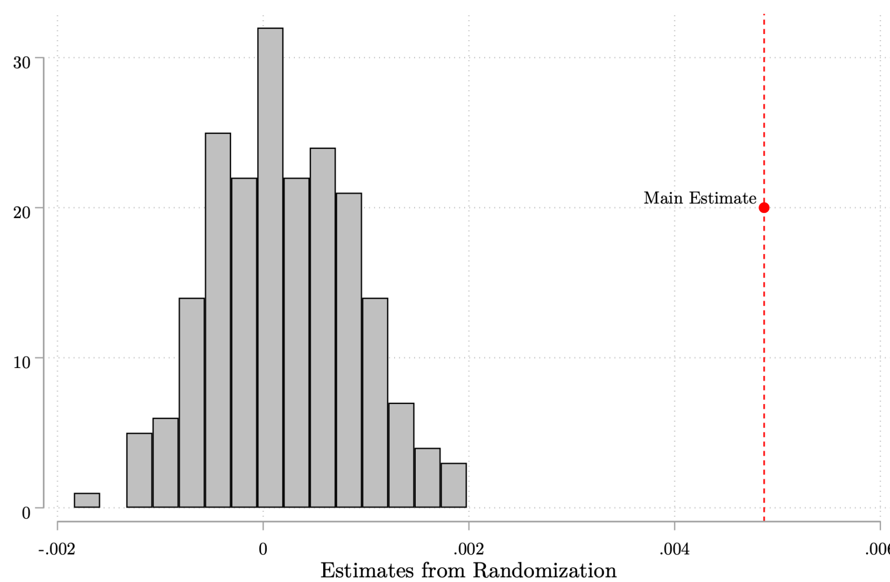
Note: Figure shows plotted coefficients from the estimation specified in Equation 3 with additional lags of particulate matter exposure included.

Figure 3: Randomization Tests

Number of Fatal Crashes



Number of Fatalities

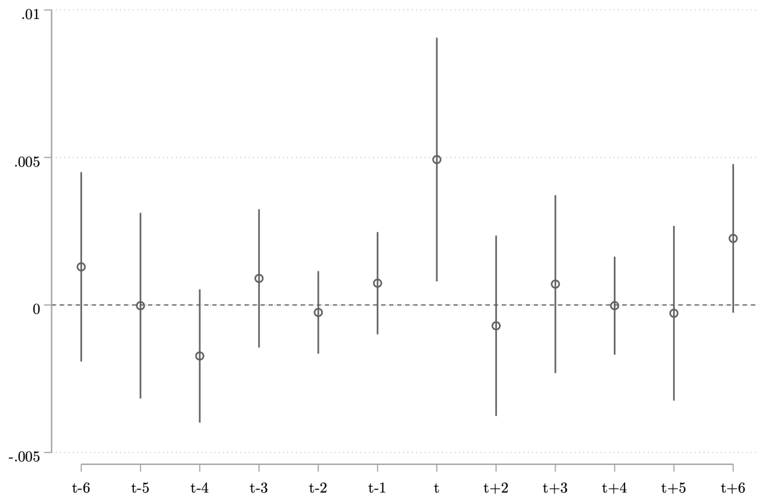


Note: Histogram plots the frequency of estimated coefficients for 200 replications of a randomization exercise in which observations for the dependent variable are randomly matched with particulate matter exposure and controls from another county. The red line plots the estimated coefficient without randomization from the estimation specified in Equation 3 shown in Table 2.

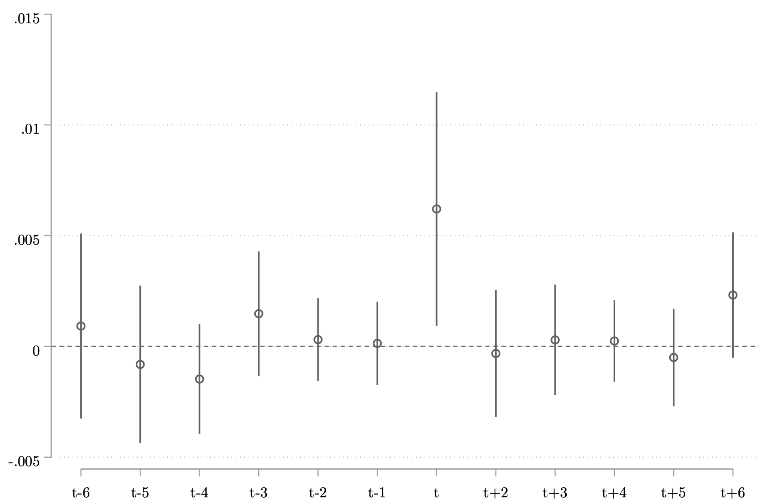
A Appendix Figures and Tables

Figure A.1: Lags and Leads of Particulate Matter Exposure

Number of Fatal Crashes



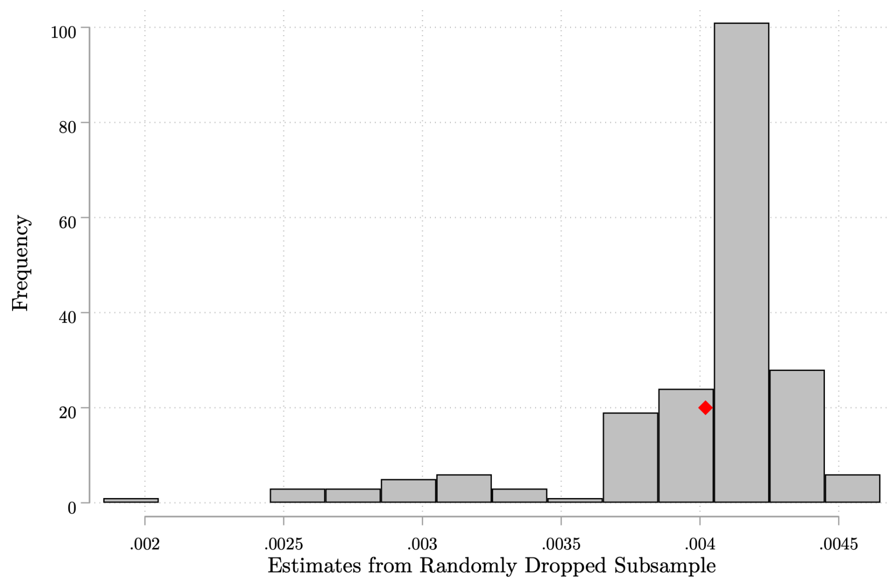
Number of Fatalities



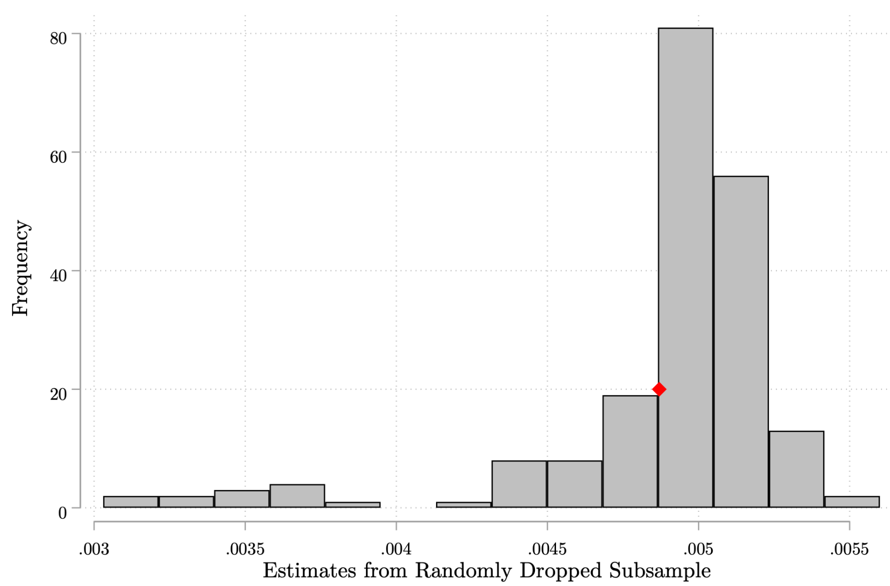
Note: Figure shows plotted coefficients from the estimation specified in Equation 3 with additional lags and leads of particulate matter exposure included.

Figure A.2: Coefficient Distribution with Randomly Dropped Subsample

Number of Fatal Crashes



Number of Fatalities



Note: Figure shows plotted coefficients from 200 iterations of the estimation specified in Equation 3 with approximately 5% of all counties randomly dropped in each iteration. Red marker indicates estimated coefficient from Table 2 with all counties included.

Table A.1: Robustness Check: More Granular Temperature Bins for Hot Days and Alternative Weather Interactions

	(1)	(2)	(3)	(4)
Fatal Crashes: $PM_{2.5}$	0.0040^{**}	0.0040^{**}	0.0037^{**}	0.0037^{**}
	(0.0016)	(0.0016)	(0.0015)	(0.0015)
Mean of Crashes	0.3688	0.3688	0.3688	0.3688
% Effect	1.09	1.09	1.01	1.00
N	1,801,586	1,801,586	1,801,586	1,801,586
Fatalities: $PM_{2.5}$	0.0049^{**}	0.0049^{**}	0.0046^{**}	0.0045^{**}
	(0.0021)	(0.0020)	(0.0020)	(0.0020)
Mean of Fatalities	0.3951	0.3951	0.3951	0.3951
% Effect	1.23	1.23	1.16	1.14
N	1,801,586	1,801,586	1,801,586	1,801,586
County-by-Month-Year FE	X	X	X	X
Day-of-week FE	X	X	X	X
Alcohol/marijuana laws		X		X
Original temperature bins	X	X		X
Finer temperature bins			X	X
Temp x precip x wind speed FE	X			
Snow x precip x wind speed FE		X	X	
Precip x wind speed FE				X

Note: Results from variations of the estimation specified in Equation 3. Outcome variables are from the Fatality Analysis Reporting System for 2005-2019 and pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019. Other control variables are the BAC limit, legality of medical and recreational marijuana, and county-by-month-year and day-of-week fixed effects. For the weather variables, each column represents one change relative to the previous column. Column 1 presents our baseline weather specification: fixed effects for two maximum temperature dummies (below freezing and above 85-degrees Fahrenheit) interacted with precipitation deciles and wind speed deciles. Column 2 controls for the same temperature dummies but does not interact them with the precipitation and wind speed deciles; rather, we add an indicator for snow and ice (maximum temperature below freezing and precipitation), and include fixed effects for that variable interacted with the precipitation and wind speed deciles. Column 3 uses the same interactions as column 2 but replaces the indicator for hot days with finer temperature bins: maximum temperature between 80-85 degrees, 85-90 degrees, 90-95 degrees, 95-100 degrees, and above 100 degrees Fahrenheit. Column 4 removes the snow-and-ice indicator and replaces the weather interaction fixed effects with precipitation deciles interacted with wind speed deciles. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.2: Robustness Checks: Effect on Traffic Stops Using All Available States

	Moving Violations	Warnings	Citations	Arrests	All Stops
	(1)	(2)	(3)	(4)	(5)
Panel A: Counts					
Effect Size $PM_{2.5}$	-0.7662	-0.4416	0.0707	0.0424	-1.2505
	(0.5004)	(0.3115)	(0.0908)	(0.0325)	(0.7729)
R^2	0.9611	0.8854	0.8642	0.8889	0.9681
Mean of Outcome	230.9331	103.8502	58.1439	19.2103	437.0430
% Effect	-0.33	-0.43	0.12	0.22	-0.29
N	361472	301434	310472	215558	361472
County FE					
County-by-Month-Year FE	X	X	X	X	X
Month-Year FE					
Day-of-week FE	X	X	X	X	X
Weather	X	X	X	X	X
Demographics					
Alcohol/marijuana laws	X	X	X	X	X

Note: Results from a variation of the estimation specified in Equation 3. The column header denotes the traffic-stop-related outcome. Panel A shows estimates for the count of each dependent variable. Column 1 estimates the effect of $PM_{2.5}$ on all traffic stops involving a moving violation. Column 2 estimates the effect on stops that result in a warning. Column 3 estimates the effect on stops that result in a citation. Column 4 estimates the effect on stops that result in an arrest. Column 5 estimates the effect on all reasons for a stop. Outcome variables are from the Stanford Open Policing Project and pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019. Other control variables are the BAC limit, legality of medical and recreational marijuana, and temperature dummy (below freezing and above 85 degrees Fahrenheit) by precipitation decile by wind speed decile fixed effects. There are also county-by-month-year and day-of-week fixed effects. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.