

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

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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 just under 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 nearly 2,000 motor vehicle fatalities in 2019.

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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 (e.g., Deryugina et al., 2019; Deryugina and Reif, 2025; 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, 2026; Danagoulain and Deza, 2025). 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

¹In 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, and emotional responses, including depression, stroke, dementia, and Parkinson’s disease (Hahad et al., 2020). One 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

²2.5 microns or 10 microns for PM_{2.5} and PM₁₀, respectively

³Per our conversations with an M.D.-Ph.D., the parts of the brain that were activated on the MRI scans include 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., 2024; 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 a 0.86% increase in the fatal motor vehicle crash rate per million population 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 number of observational units is large.

We also measure how traffic fatalities respond to differences in particulate matter pollu-

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

tion. Fatalities are an important outcome in their own right as, ultimately, from a policy 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 also associated with a 0.86% increase in the traffic fatality rate per million population. Put differently, a one-standard-deviation increase in $PM_{2.5}$ corresponds to a 5.5% increase in the motor vehicle fatality rate. The increase in the fatality rate is driven largely by deaths resulting from impulsive driving as opposed to those resulting from cognitive errors or for those deemed not at fault for the crash. Our estimates imply that reducing pollution exposure by one standard deviation across the board would avert nearly 2,000 motor vehicle fatalities every year. We quantify the effect of reducing fine particulate matter pollution by this amount to be worth \$18.6 billion dollars per year on the basis of reduced motor vehicle fatalities alone, which does not include reductions in other causes of death, health and labor-market productivity improvements, and other benefits of reduced pollution.

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 pollution exposure 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. 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- $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$, and that this effect can last for up to two days. Interestingly, Shr et al. (2023), using data from Taiwan, find that a one- $\mu\text{g}/\text{m}^3$ change is associated with a 0.59% decrease, which 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 $\mu\text{g}/\text{m}^3$ 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 the effects of wildfire plumes on motor vehicle collisions in counties in the American West, finding 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 $\text{PM}_{2.5}$ readings and data from the Fatality Analysis Reporting System as we do here. 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. 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 due to climate change, 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 2005, the first year of court-ordered enforcement of the 1990 update to the Clean Air Act, and 2019, the last year of the sample. 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: 20.5% of counties in 2005 and 19.5% of counties in 2019 meet these criteria. The bottom-left corner, in contrast, shows 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, which reflects how much progress has been made in reducing $PM_{2.5}$ emissions over the sample period. In 2005 the highest average $PM_{2.5}$ is 20.1 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 17.4 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 $12 \mu\text{g}/\text{m}^3$, 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

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, 2025). 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.^{5,6,7} However, these monitors are located in more populated areas, which make up a majority of

⁵Some 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.

⁶Depending 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.

⁷Strategic misreporting of pollution data has also been documented by Zou (2021) and Mu et al. (2024). Our IV strategy helps account for this source of measurement error.

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 $\text{PM}_{2.5}$ concentration is $9.77 \mu\text{g}/\text{m}^3$, 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 79 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 $5.81 \mu\text{g}/\text{m}^3$ on average with a maximum within-county standard deviation of $17.0 \mu\text{g}/\text{m}^3$.

We couple our particulate pollution information with wind speed and direction data from the North American Regional Reanalysis daily reanalysis data.⁸ 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 in from the water. Alternatively, suppose that a neighboring county produces particulate matter pollution through industrial activity, power generation,

⁸These data are collected using the climateR package by Johnson (2022).

or high car density. When the wind blows from the direction of the polluting county it will bring in higher particulate matter concentrations. These exogenous changes in wind direction allow us to address the simultaneous determination problem – more cars result in more crashes and more cars result in more particulate pollution, but we are trying to determine whether more pollution causes more crashes.

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 lead to more car crashes (Baylis, 2020; Colmer and Doleac, 2026).⁹ We also control for precipitation

⁹In Appendix Table A.1, we present results that account for different interactions of the weather variables and potentially non-linear effects of temperatures by controlling for more granular variations in temperature. The estimates are robust to including more granular indicators for the maximum daily temperature with temperature bins of 80-85 degrees, 85-90 degrees, 90-95 degrees, 95-100 degrees, and 100+ while still including

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, 2025). We aggregate crash and fatality data to the county-day level, and convert to rates per million population using annual county-level population estimates from the Census Bureau’s County Intercensal Estimates (U.S. Census Bureau, 2025). 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).

an indicator for days below freezing. Moderate days (those below 80 degrees but above freezing) are our omitted group.

2.2 Econometric Specification

We estimate both OLS and instrumental variables specifications, using *reghdfe* (Correia, 2017). 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:

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

F_{cymd} denotes the fatality or fatal car crash rate (per million population) 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 . $\mathbf{X}_{\mathbf{cymd}}$ 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.¹⁰

Our primary sample period runs from April 2005 to December 2019. We start in April 2005, when the 1990 Clean Air Act standards began to be enforced, so that our variation

¹⁰We 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.

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 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 (e.g., Deryugina et al., 2019; Persico and Marcotte, 2022).

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

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

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 crash and motor vehicle fatality rates using the following IV specification; \widehat{AP}_{cymd} is the predicted measure of air pollution from Equation 2:

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

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- $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ is associated with a daily increase of 0.0005 fatal crashes per million population. This effect is small and statistically significant at the 1% level, representing a 0.20% increase. Including time-varying controls attenuates the estimate: a one- $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ is associated with a 0.0001 increase in the fatal crash rate, which is not significant. The effect of air pollution on the motor vehicle fatality rate is quantitatively and qualitatively similar to the effect on the fatal crash rate. In the specification with controls (Column 2), a one- $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ leads to an increase of 0.0001 fatalities per million population 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 $\text{PM}_{2.5}$ concentration on wind direction are orders of magnitude larger than the threshold for valid inference (Lee et al., 2022). A one- $\mu\text{g}/\text{m}^3$ increase in predicted $\text{PM}_{2.5}$ leads to an increase in the daily fatal crash rate of 0.0025. This effect is statistically significant at the 1% level and represents a 1.12% increase in the fatal crash rate. The effect size is similar when we add in weather and policy controls (Column 2, our preferred specification): an increase of 0.0020, or 0.86%.

The results for fatalities mirror those for crashes. In the version with controls (Column 2), a one- $\mu\text{g}/\text{m}^3$ increase in predicted $\text{PM}_{2.5}$ leads to a 0.86% increase in the fatality rate. For context, a one-standard-deviation increase in $\text{PM}_{2.5}$ corresponds to a 5.5% increase in the motor vehicle fatality rate.

3.3 Robustness Checks

Our results are robust to alternative functional form specifications, specifically a linear probability model, pseudo-maximum-likelihood Poisson specification, and inverse hyperbolic sine specification, as shown in Table 3. The results are sensitive to the use of weights and to switching out rates for counts of crashes and fatalities. 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 count of crashes and fatalities. In Column 3, we estimate a pseudo-maximum likelihood Poisson specification using the control-function approach: we include the residuals from the first-stage regression as a control variable and instead of weighting by population use population as the exposure variable. Column 4 transforms the outcome variable using the inverse hyperbolic sine. In Column 5, the OLS-IV regression results (with rates as the outcome variable) are unweighted. In Column 6, we generate our measure of predicted pollution using the CDC’s modeled satellite data. In this last specification, to be consistent with the main specifications we restrict the sample to counties with EPA monitors, giving us the same county coverage but a balanced panel (every day).

We find that a one-unit increase in predicted $PM_{2.5}$ leads to a 0.16 percentage point increase in the probability of any fatal crashes or fatalities, a 0.62% increase that is significant at the 5% level (Column 1). When expressed as a count (Column 2) we estimate a 0.59% and 0.71% increase for each outcome, respectively, although these effects are not statistically significant. When we estimate a pseudo-maximum likelihood Poisson specification (Column 3), we find an increase of 0.0016 crashes and 0.0017 fatalities per day, a 0.43% increase relative to the mean for both. 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- $\mu g/m^3$ increase in $PM_{2.5}$ leads to an increase of 0.0018 crashes and 0.0020

fatalities (0.49% and 0.51%), which are both marginally significant. The unweighted OLS-IV regressions (Column 5) yield similar but less-precise effect sizes relative to the weighted OLS-IV regressions, which is not surprising. A unit increase in $PM_{2.5}$ leads to an increase in the crash and fatality rate of 0.0026 and 0.0018, respectively. These effects correspond to a 0.75% and 0.46% increase over the mean but are not statistically significant. Lastly, we make use of satellite-based gridded atmospheric data (Centers for Disease Control and Prevention, 2021) that provide a more comprehensive and complete series of particulate matter data (Column 6). These data have wider spatial coverage and recordings for every day, but are only available from 2001-2016.¹¹ To be consistent with our main specification, we restrict the CDC sample to the same counties covered by the EPA monitors and start the sample period in April 2005, post-Clean-Air-Act enforcement.¹² In this specification, we find a statistically significant increase in both crashes and fatalities at the 5% level, and the point estimates are slightly attenuated relative to the main estimates: a one-unit increase in $PM_{2.5}$ leads to an increase in the crash and fatality rate of 0.0014. These effects correspond to a 0.57% and 0.53% increase over the mean crash and fatality rates.

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 $PM_{2.5}$.¹³ For these regressions, we use actual $PM_{2.5}$, as

¹¹The 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).

¹²The number of observations increases to more than 3 million using these new data for particulate matter concentrations.

¹³We do not further parse the highest bin due to a lack of statistical power: less than 0.5% of the sample

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.¹⁴ We replace them with county and month-year fixed effects, the monthly unemployment rate from the BLS (Bureau of Labor Statistics, 2025), and annual demographic variables from the Census (U.S. Census Bureau, 2025): the fraction of the population that is Black, Hispanic, other (non-white) races, male and between the ages of 15 and 24, male and other ages, and female and between the ages of 15 and 24.¹⁵ 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. Columns 2 and 4 represent Columns 1 and 3 of Table 4 with the alternate control variables. 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 the crash and fatality rate is small (0.0001) and not significant. On days where the air quality index is in the upper end of the “good” range, the crash and fatality rates increase by 0.0060 and 0.0058 relative to days where the air quality index is in the lower end of the “good” range; this effect is statistically significant at the 1% level. On days with moderate air quality, the crash and fatality rates increase by 0.0078 and 0.0083, respectively. These results are also significant at the 1% level. On days when the air quality for $PM_{2.5}$ ranges from unhealthy for sensitive groups to hazardous, the crash and fatality rates increase by 0.0127 and 0.0140; these effect sizes are marginally 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

has a recorded air quality worse than “moderate”, and less than 0.1% has a recorded air quality in the unhealthy or worse range.

¹⁴Large wildfires mostly occur in the late summer and fall in Western and Mountain West states.

¹⁵Omitted demographic categories are the fraction of the population that is white and the fraction of the population that is female and other ages.

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, that may indicate additional mechanisms by which pollution affects driving beyond real-time cognitive effects (e.g., poor sleep quality or respiratory distress). Figure 2 shows plotted coefficients from our fully specified model while also including lags of predicted 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 mechanisms 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.

We next explore the robustness of the results to alternative specifications of the temperature controls and different interactions of the weather variables. Our primary specification interacts precipitation and wind speed deciles with indicators for below-freezing temperatures and hot days: the former to account for snow and ice, and the latter to account for any effects of heat on temperament and aggression (Baylis, 2020; Colmer and Doleac, 2026). A potential concern is that wind direction may influence both temperature and pollution, which would be a threat to the exclusion restriction if wind direction affected crashes and fatalities through temperature in addition to pollution. We are not concerned about this threat to the exclusion restriction for two reasons. First, potential correlation between temperature and pollution would be concerning if wind direction brought in increased pollution in conjunction with temperature ranges that could plausibly be associated with increases in crashes (e.g., wind from one direction bringing in high pollution on very hot days). Instead,

high-pollution wind direction is correlated with cold air movement. Second, much of the exogenous variation that the instrument captures relates to changes in inversion conditions in which pollutants can be more easily trapped in an area, which is a mechanism by which wind direction affects pollution levels.¹⁶

These temperature robustness checks are presented in Appendix Table A.1. Our results are robust to using average instead of maximum temperatures for our temperature bins (Column 2), using finer temperature bins at the top of the temperature spectrum (Column 3), and to similar temperature bins as those used in Sager (2019) (Column 5).¹⁷ Our results are not robust to temperature deciles (Column 4), including temperature in a cubic spline form (Column 6), or including average daily temperature linearly (Column 7) or quadratically (Column 8). This lack of robustness is not surprising, as these specifications likely over-absorb variation driven by wind patterns, creating collider bias by nullifying the variation captured by the wind instrument.

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 crash and fatality rates 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

¹⁶Inversions can be caused by several factors, but the two most common are radiational cooling and frontal inversions. Inversions create stable atmospheric conditions where warmer air sits above cooler air, trapping pollutants near the surface. In our setting, including granular temperature controls introduces collider bias. Small changes in low-moderate (but above-freezing) temperatures are not predictive of anger, aggression, or worse road conditions, but they are influential in changing local inversion conditions and air trapping. In other words, our instrument (wind patterns) affects the outcome through pollution, and temperature is part of the causal mechanism linking pollution to outcomes, not an independent pathway that violates the exclusion restriction.

¹⁷Sager (2019) divides temperatures into 5 bins (Celsius): 0-5, 5-10, 10-15, and > 15 , where below freezing is the omitted group. As we use Fahrenheit, we instead use 32-40, 40-50, 50-60, and > 60 , with below freezing as the omitted group.

the model specified in Equation 3 for each random draw for both crash and fatality rates.¹⁸ This test is able to determine if there is model-induced bias (Hsiang and Jina, 2014). Figure 3 plots the histogram of z-statistics with randomized matching as well as the z-statistic using non-randomized data from Table 2 (the red vertical line). The average z-statistic across randomized model estimates is 0.214 and 0.318 for the number of fatal crashes per million and number of fatalities per million people, respectively, which shows that the effect of pollution on car crashes and fatalities is not due to chance or model-driven bias.

Next, we test whether some observations are overly influential in estimating 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 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. The mean effect size for the crash rate across iterations is 0.0020.¹⁹ All of the 200 iterations are statistically significant at at least the 5% level. For the fatality rate, the mean effect size across iterations is 0.0021.²⁰ These are similarly all statistically significant at the 5% level or better. We conclude from these randomization tests that our result is not sensitive to removing particular counties.

¹⁸A total of 400 random matches across both outcome variables.

¹⁹Corresponding to a mean z-statistic of 2.78.

²⁰Corresponding to a mean z-statistic of 2.65.

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 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 the fatality rate of drivers who were at fault for any reason: a one-unit increase in $PM_{2.5}$ leads to an increase of 0.0009 fatalities per million, a 1.00% effect that is statistically significant at the 5% level. This effect size is largely driven by fatalities of drivers that were engaging in impulsive behaviors: the fatality rate increases by 0.0007 (1.49%), an effect that is statistically significant at the 5% level (Column 2). The fatality rate for drivers who made cognitive errors also increases, by 0.0004 (0.72%), but this increase is not statistically significant (Column 3). The fatality rate for those not at fault, defined as drivers who did not engage in behaviors that contributed to the crash or non-drivers, is a statistically insignificant 0.0006 increase (0.64%; Column 4). The increase in fatalities of at-fault, particularly impulsive, drivers, 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 the drunk-driver-related (Column 1) and alcohol-related (Column 2) fatality rates, increasing fatalities by 0.0004 (1.48%) and 0.0005 (1.59%) per million, respectively. The former is marginally statistically significant and the latter is statistically significant at the 5% level. 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, as opposed to drivers with positive but lower blood alcohol concentrations. Turning to pedestrian and cyclist fatalities (Columns 3 and 4), higher pollution does not have a statistically significant effect on the pedestrian or cyclist fatality rates, although in percentage terms, the effect sizes are similar to the effects on the overall fatality rate. 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.

Turning to fatality rates 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 64.²¹ 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

²¹The 2000 to 2010 Intercensal County Population Estimates only have population estimates in 5-year age bins (e.g., 15 to 19, 20 to 24). To construct the population estimates for the “less than 16”, “16 to 64”, and “16 to 24” age bins for 2005 to 2009, we assume there are an equal number of 15, 16, 17, 18, and 19-year-olds in the 15 to 19 age bin. We use the 2010 to 2020 Intercensal estimates for 2010 and later, which do include population estimates for the entire 16 and older population.

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 the fatality rate for prime-age adults: an increase of 0.0028 for 16 to 64 year-olds (0.94%, Column 2), which is significant at the 5% level. This increase in the fatality rate is driven by the 25-to-34 age group, and to a lesser extent the 35-to-64 age group: the fatality rate for 25-to-34-year-olds increases by 0.0056 (1.73%; significant at the 1% level) and that for 35-to-64-year-olds increases by 0.0024 (0.91%; marginally 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), and also shows how pollution can be fatal for a broad range of ages.

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 represents a stop, and for some states, the outcome of the stop is also recorded: a warning, citation, or arrest. 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 seven states that have data available for all outcome variables at the

county level to daily counts.²² 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, expressed as rates per million population, are the total number of stops that are the most common moving violations, the number of warnings issued for all stops, the number of citations issued for all stops, the number of arrests made for all stops, and the total number of stops.²³ On an average day, there are 601 stops in a county (corresponding to 236 stops per million population). Of these, 321 are due to a common moving violation (127 per million population), 110 stops result in a warning (51 per million population), 55 stops result in a citation (45 per million population), and 19 stops result in an arrest (7 per million population). 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 types changes. For example, if higher pollution leads to more extreme or reckless driving, the proportion of citations or arrests relative to all stops may increase.

Panel A of Table 7 shows the effect of a one- $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ on the rate 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 effect of an increase in $\text{PM}_{2.5}$ on the proportion of each stop type or outcome relative to all stops in a day.²⁴ Particulate matter exposure has precisely estimated null effects on common

²²These states are Arizona, California, Florida, Michigan, Montana, North Carolina, and Wisconsin.

²³The most commonly and consistently recorded moving violations across states are speeding, careless or reckless driving, any kind of stop that is related to 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.

²⁴Appendix Table A.2 expands the sample to include 18 states with data on the specific violation that occurred. For this table we are able to differentiate between moving violations and all violations, but not

moving violations, warnings, citations, arrests, and all stops. For the larger sample presented in Appendix Table A.2, we find a statistically significant but very small reduction in common moving violations (0.42%, and we can rule out reductions larger than 0.78% with the 95% confidence interval) and precisely estimated null effects for the other four outcomes. 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 of Table 7, there is some evidence that the mix of stop outcomes shifts towards citations and away from warnings, but the effect sizes are again quite small: a 0.27% increase in the proportion of citations and a 0.22% decrease in the proportion of warnings.

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 the rate of fatal crashes and fatalities, building on prior work which has mostly been at the sub-national level or focused on other countries.²⁵ To

every state records whether a warning, citation, or arrest occurred. We do not show estimates for the proportion of each occurrence for these states, because state differences in data collection practices may bias the results.

²⁵Sager (2019), Shi et al. (2022), Baryshnikova and Wesselbaum (2023), Shr et al. (2023), Braun and Villas-Boas (2024), Firsova (2025).

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 lingering effects of exposure. Contemporaneous exposure increases both fatal motor vehicle crashes and fatalities, but pollution exposure over the prior week does not. 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. 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 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. 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, 2025), 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 (in 2006 dollars) as the value of a statistical life; 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. We find a one $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ leads to 0.0021 additional deaths per million people, an increase of 0.86% relative to the mean. A one-standard-deviation increase in $\text{PM}_{2.5}$ ($6.34 \mu\text{g}/\text{m}^3$) corresponds to a 5.5% increase in motor vehicle fatalities, or one additional death per million people every 80 days (approximately 4 additional deaths per million people in a year). For areas affected by wildfires or heavy industrial activity, it is not abnormal for daily particulate matter levels to spike by upwards of $10 \mu\text{g}/\text{m}^3$ with poor air quality persisting for a substantial period of time.

How do these effect sizes compare to other determinants of fatal crashes? A 1-unit, or approximately 10%, increase in $\text{PM}_{2.5}$ increases the fatality rate by 0.86% whereas a 10% increase in seatbelt use decreases fatalities by 1.3%, making the effect of pollution approximately two-thirds as large (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 $\text{PM}_{2.5}$ corresponds to a 5.5% increase in motor vehicle fatalities. Consequently, an across-the-board one-standard-deviation reduction in fine particulate matter pollution would have prevented nearly 2,000 motor vehicle fatalities in 2019. Using the EPA’s value of a statistical life, the pollution abatement efforts required would yield

benefits of \$18.6 billion per year on the basis of fewer motor vehicle fatalities alone, which excludes reductions in other causes of death.²⁶ In February 2024, the EPA lowered PM_{2.5} standards from 12 to 9 $\mu\text{g}/\text{m}^3$. Our research suggests this new standard will save lives.

²⁶The EPA’s \$7.4 million estimate is in 2006 dollars, and they recommend updating the dollar amount to the year of the analysis (Environmental Protection Agency, 2026). We convert \$7.4 million into 2019 dollars using the Minneapolis Fed’s inflation calculator, which is based off the CPI-U (Federal Reserve Bank of Minneapolis, 2026).

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5 Tables

Table 1: Summary Statistics

	(1)
PM _{2.5} Concentration ($\mu\text{g}/\text{m}^3$)	9.7669 (6.3414)
Number of Crashes	0.3691 (0.7710)
Number of Fatalities	0.3955 (0.8503)
Crashes (Rate per Million Population)	0.2265 (0.8995)
Fatalities (Rate per Million Population)	0.2442 (1.0403)
Maximum Daily Temperature (Degrees F)	69.3893 (18.5058)
Daily Precipitation (Inches)	0.1045 (0.2939)
Blood Alcohol Concentration Limit	0.0800 (0.0011)
Medical Marijuana Legal	0.4943 (0.5000)
Recreational Marijuana Legal	0.0976 (0.2967)
Unemployment Rate	0.0608 (0.0276)
Fraction Black	0.1427 (0.1279)
Fraction Hispanic	0.2190 (0.1745)
Fraction Other Races	0.0966 (0.0726)
Fraction White	0.5418 (0.2069)
Fraction Male Other Ages	0.4193 (0.0128)
Fraction Male 15-24	0.0709 (0.0112)
Fraction Female 15-24	0.0684 (0.0109)
Fraction Female Other Ages	0.4414 (0.0144)
Observations	1,796,253

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

	(1)	(2)
<i>Panel A: OLS Results</i>		
Fatal Crashes (Rate per Million)	0.0005*** (0.0001)	0.0001 (0.0001)
Mean Crash Rate	0.2265	0.2265
% Effect	0.20	0.05
N	1,796,114	1,796,114
Fatalities (Rate per Million)	0.0005*** (0.0001)	0.0001 (0.0001)
Mean Fatality Rate	0.2442	0.2442
% Effect	0.20	0.05
N	1,796,114	1,796,114
<i>Panel B: Instrumental Variables Results</i>		
Fatal Crashes (Rate per Million)	0.0025*** (0.0005)	0.0020*** (0.0007)
Mean Crash Rate	0.2265	0.2265
% Effect	1.12	0.86
N	1,796,114	1,796,114
Fatalities (Rate per Million)	0.0026*** (0.0006)	0.0021*** (0.0008)
Mean Fatality Rate	0.2442	0.2442
% Effect	1.07	0.86
N	1,796,114	1,796,114
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. Each coefficient is from a separate regression. The F-statistics for the first-stage regressions are 112,260 for predicted PM_{2.5} under the more parsimonious specification (Panel B, Column 1), and 138,154 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. The fatal crash rate and fatality rate represent crashes and fatalities per million population. 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: Alternative Functional Form Specifications and CDC Modeled Satellite Data

	LPM	Count	Pseudo- Maximum Likelihood Poisson	IHS	Not Weighted	CDC Satellite Data
	(1)	(2)	(3)	(4)	(5)	(6)
Fatal Crashes	0.0016** (0.0007)	0.0022 (0.0014)	0.0016*** (0.0005)	0.0018* (0.0010)	0.0026 (0.0028)	0.0014** (0.0006)
Mean of Crashes	0.2502	0.3691	0.3691	0.3691	0.3462	0.2408
% Effect	0.62	0.59	0.43	0.49	0.75	0.57
N	1,796,114	1,796,114	1,111,644	1,796,114	1,796,114	3,326,464
Fatalities	0.0016** (0.0007)	0.0028 (0.0017)	0.0017*** (0.0006)	0.0020* (0.0011)	0.0018 (0.0035)	0.0014** 0.0007
Mean of Fatalities	0.2502	0.3955	0.3955	0.3955	0.3796	0.2614
% Effect	0.62	0.71	0.43	0.51	0.46	0.53
N	1,796,114	1,796,114	1,111,644	1,796,114	1,796,114	3,326,464
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 variations of the estimation specified in Equation 3. The column header denotes the functional form specification or pollution data source and the row header denotes the outcome variable. Column 1 estimates a linear probability model where the outcome is whether any crashes or fatalities occur. Column 2 uses the count of crashes or fatalities. Column 3 estimates a pseudo-maximum likelihood Poisson specification using the count of crashes or fatalities in a control-function approach. Column 4 uses an inverse hyperbolic sine transformation of the outcome variable. Column 5 presents unweighted OLS-IV regression results using rates as the outcome. 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 5) or the Centers for Disease Control for 2005-2016 (column 6). 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: Heterogeneous Effects by Concentrations of PM_{2.5}

	OLS (1)	OLS (2)	IV (3)	IV (4)	OLS (5)
<i>Panel A: Fatal Crashes (Rate per Million)</i>					
PM _{2.5}	0.0001 (0.0001)	0.0001 (0.0001)	0.0020*** (0.0007)	0.0014** (0.0007)	
PM _{2.5} Upper Half of Good Range					0.0060*** (0.0018)
PM _{2.5} Moderate					0.0078*** (0.0018)
PM _{2.5} Unhealthy for Sensitive Groups or Worse					0.0127* (0.0067)
Mean Crash Rate	0.2265	0.2265	0.2265	0.2265	0.2265
% Effect	0.05	0.06	0.86	0.60	
N	1,796,114	1,795,542	1,796,114	1,795,542	1,795,542
<i>Panel B: Fatalities (Rate per Million)</i>					
PM _{2.5}	0.0001 (0.0001)	0.0002 (0.0001)	0.0021*** (0.0008)	0.0012* (0.0007)	
PM _{2.5} Upper Half of Good Range					0.0058*** (0.0019)
PM _{2.5} Moderate					0.0083*** (0.0020)
PM _{2.5} Unhealthy for Sensitive Groups or Worse					0.0140* (0.0080)
Mean Fatality Rate	0.2442	0.2442	0.2442	0.2442	0.2442
% Effect	0.05	0.06	0.86	0.50	
N	1,796,114	1,795,542	1,796,114	1,795,542	1,795,542
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 $\mu\text{g}/\text{m}^3$ 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 reproduce 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. The fatal crash rate and fatality rate represent crashes and fatalities per million population. 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)
<i>Panel A</i>				
Fatalities (Rate per Million)	0.0009** (0.0004)	0.0007** (0.0003)	0.0004 (0.0003)	0.0006 (0.0005)
Mean Fatality Rate	0.0905	0.0497	0.0585	0.0944
% Effect	1.00	1.49	0.72	0.64
<i>N</i>	1,796,114	1,796,114	1,796,114	1,796,114
	Drunk (1)	Alcohol-Related (2)	Pedestrian (3)	Cyclist (4)
<i>Panel B</i>				
Fatalities (Rate per Million)	0.0004* (0.0002)	0.0005** (0.0002)	0.0004 (0.0003)	0.0001 (0.0001)
Mean Fatality Rate	0.0237	0.0302	0.0502	0.0070
% Effect	1.48	1.59	0.87	1.64
<i>N</i>	1,796,114	1,796,114	1,796,114	1,796,114
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	X	X
Demographics				
Alcohol/marijuana laws	X	X	X	X

Note: Results from a variation of the estimation specified in Equation 3. The column header denotes the outcome variable. All effects represent fatalities per million population. 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 on 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 (1)	16-64 (2)	65+ (3)	16-24 (4)	25-34 (5)	35-64 (6)
Fatalities (Rate per Million)	0.0002 (0.0006)	0.0028** (0.0011)	0.0016 (0.0023)	0.0011 (0.0026)	0.0056*** (0.0020)	0.0024* (0.0012)
Mean Fatality Rate	0.0438	0.2975	0.2950	0.3938	0.3218	0.2603
% Effect	0.45	0.94	0.55	0.28	1.73	0.91
N	1,796,114	1,796,114	1,796,114	1,796,114	1,796,114	1,796,114
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 fatality rates by age (fatalities per million population in that age range). Column 1 estimates the effect for ages less than 16. Column 2 estimates the effect for ages 16 to 64. Column 3 estimates the effect for ages 65 and older. Columns 4 through 6 break down the 16-64 fatality rates 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: Effect on Traffic Stops

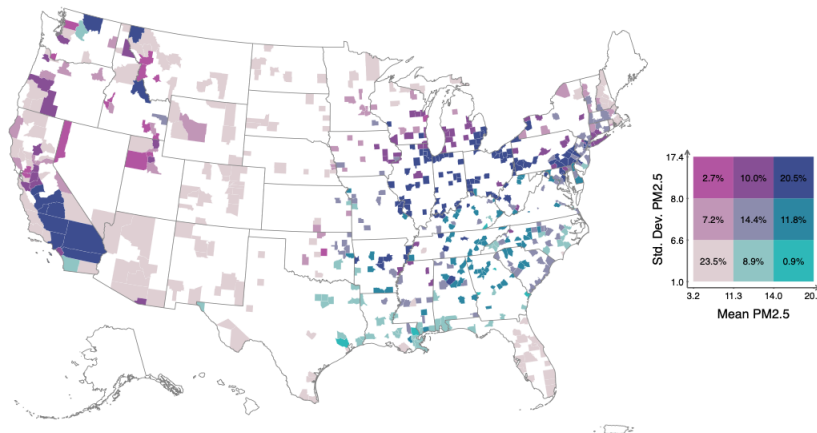
	Moving Violations	Warnings	Citations	Arrests	All Stops
	(1)	(2)	(3)	(4)	(5)
<i>Panel A: Rate per Million Population</i>					
Effect Size	-0.2886 (0.2275)	-0.0691 (0.0925)	0.0949 (0.1187)	-0.0065 (0.0139)	-0.4413 (0.3395)
Mean of Outcome	126.5654	51.2173	45.4247	7.0518	235.6858
% Effect	-0.23	-0.13	0.21	-0.09	-0.19
<i>N</i>	218,103	218,103	218,103	218,103	218,103
<i>Panel B: Proportion of All Stops</i>					
Effect Size	-0.0810 (0.0602)	-0.0543* (0.0291)	0.0713** (0.0317)	-0.0020 (0.0161)	- -
Mean of Outcome	55.5253	24.3503	26.2608	2.9657	-
% Effect	-0.15	-0.22	0.27	-0.07	-
<i>N</i>	218,103	218,103	218,103	218,103	-
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 sample includes traffic stop data from the following states: Arizona, California, Florida, Michigan, Montana, North Carolina, and Wisconsin. These seven states record every type of stop outcome listed (warnings, citations, and arrests). The column header denotes the traffic-stop-related outcome. The effects in Panel A represent stops per million population. 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 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 all stops that result in a warning. Column 3 estimates the effect on all stops that result in a citation. Column 4 estimates the effect on all stops that result in an arrest. Column 5 estimates the effect on all stops. The effects in Panel B represent the proportion of all stops, measured in percentage points (e.g., number of moving violations/number of stops*100). 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

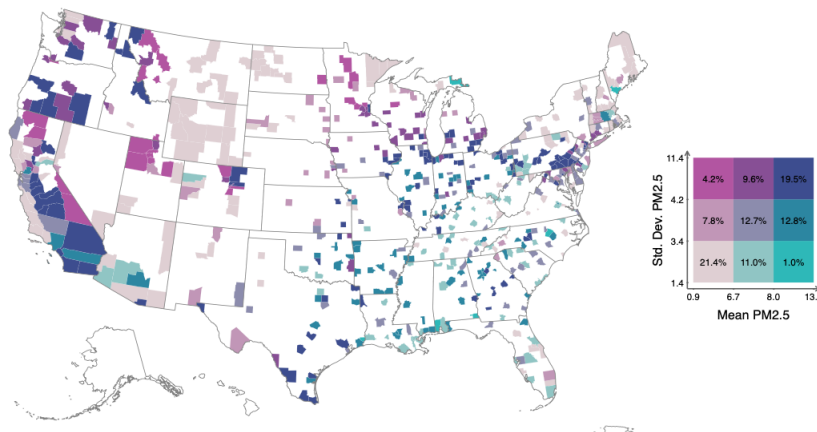
6 Figures

Figure 1: Pollution Variation Over Time and Geography

2005



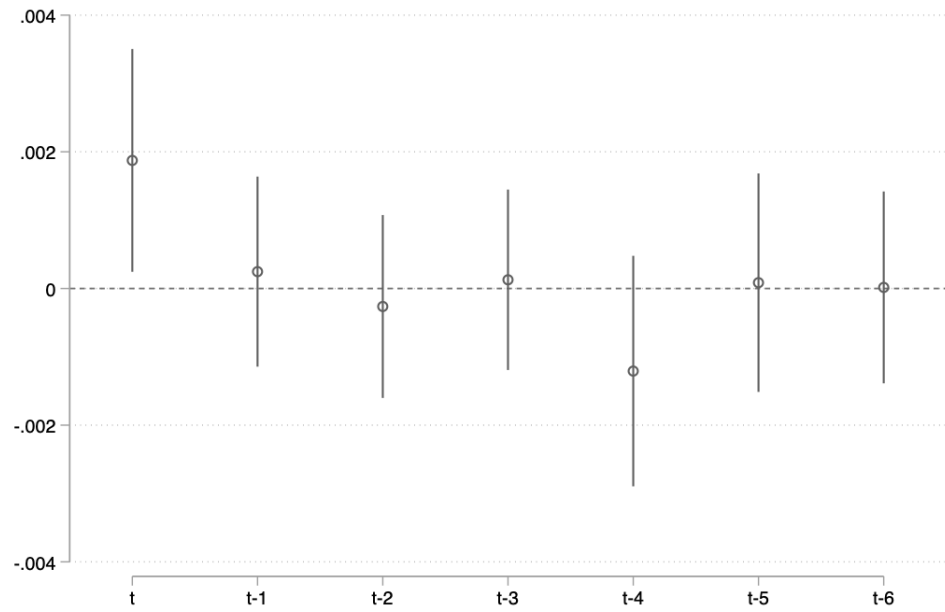
2019



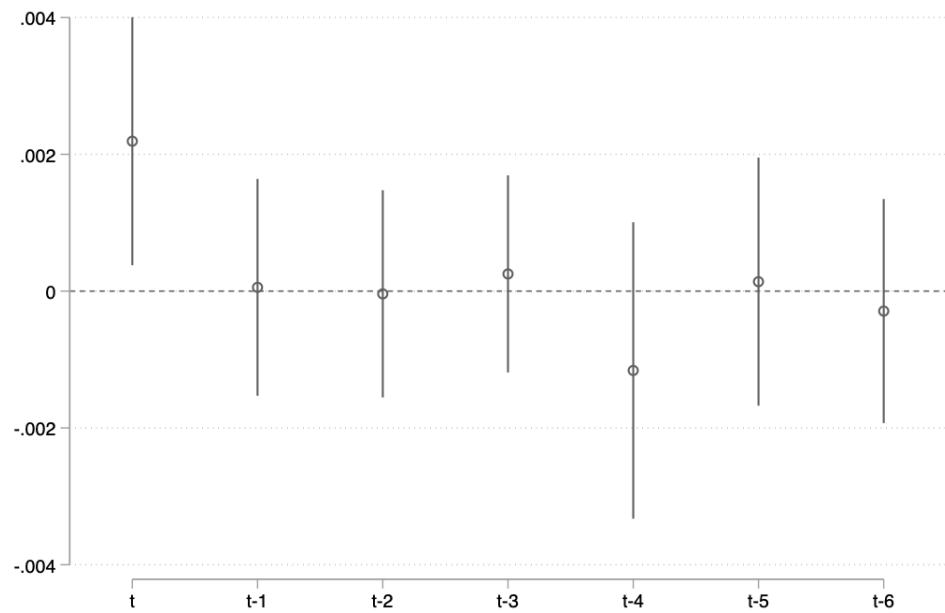
Note: The figure shows the within-county average annual $PM_{2.5}$ concentrations and standard deviations for the first and last years of the sample: 2005 and 2019. The color scale on the right-hand axis splits each variable into equal thirds (each column or row adds up to 33.3%). Values show the percent of counties that belong to each average-standard deviation pair. For example, the top-right corner includes counties in the highest third for both $PM_{2.5}$ concentration and standard deviation, while the bottom-left corner includes counties in the lowest third for both measures.

Figure 2: Effects of Lagged Particulate Matter Exposure

Fatal Crashes (Rate per Million Population)



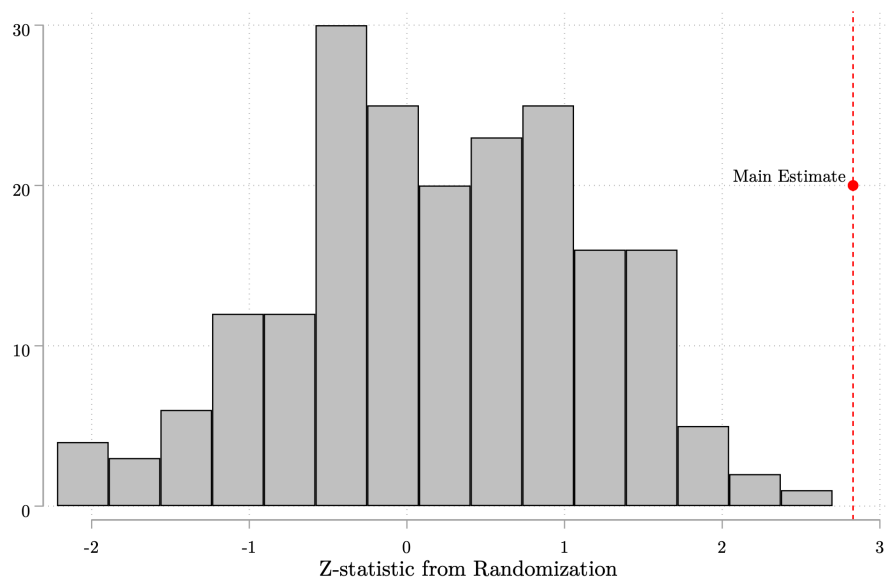
Fatalities (Rate per Million Population)



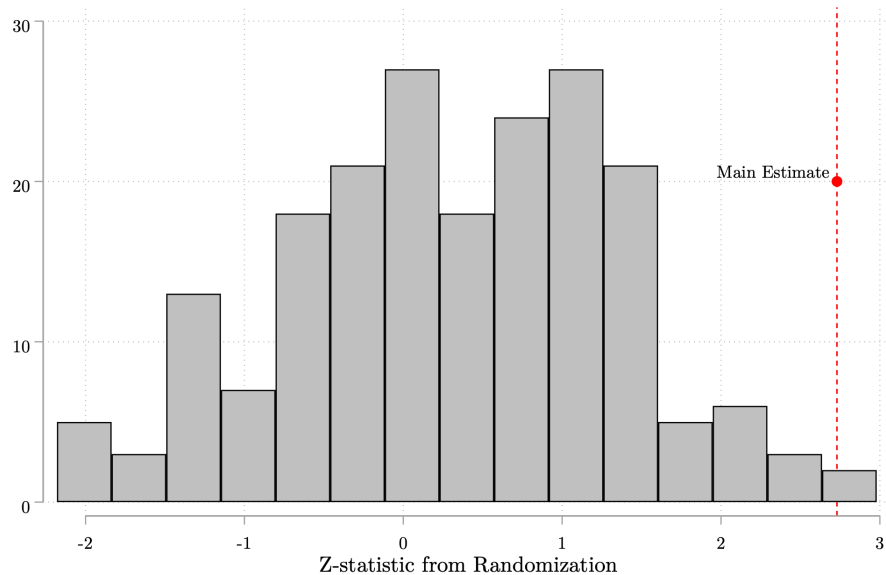
Note: Figure shows plotted coefficients from the estimation specified in Equation 3 with additional lags of predicted particulate matter exposure for each day over the previous week included.

Figure 3: Falsification Test: Randomly Matching One County's Outcomes to Another County's Predicted Pollution and Controls

Fatal Crashes (Rate per Million Population)



Fatalities (Rate per Million Population)

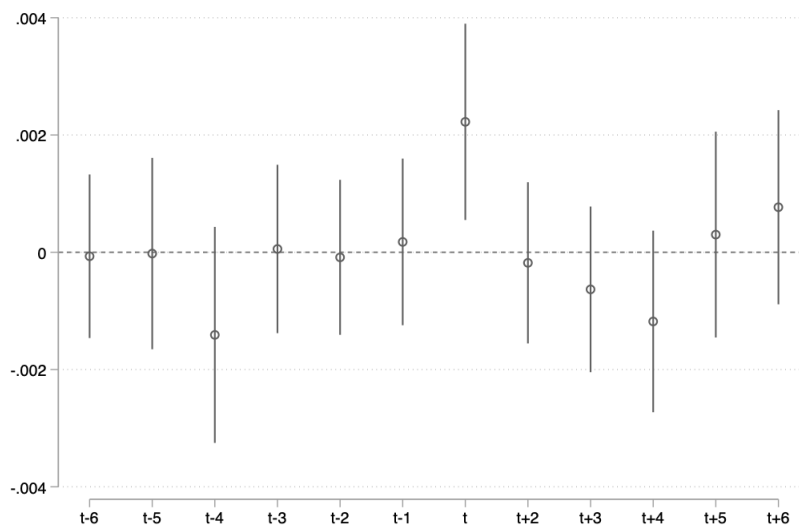


Note: Histograms plot the distribution of z-statistics corresponding to estimated effects from 200 replications of a randomization exercise in which observations for the dependent variable (the crash and fatality rate) are randomly matched with predicted $PM_{2.5}$ concentrations and control variables from another county. The red line plots the z-statistic corresponding to the results from the estimation specified in Equation 3 shown in Column 2 of Table 2.

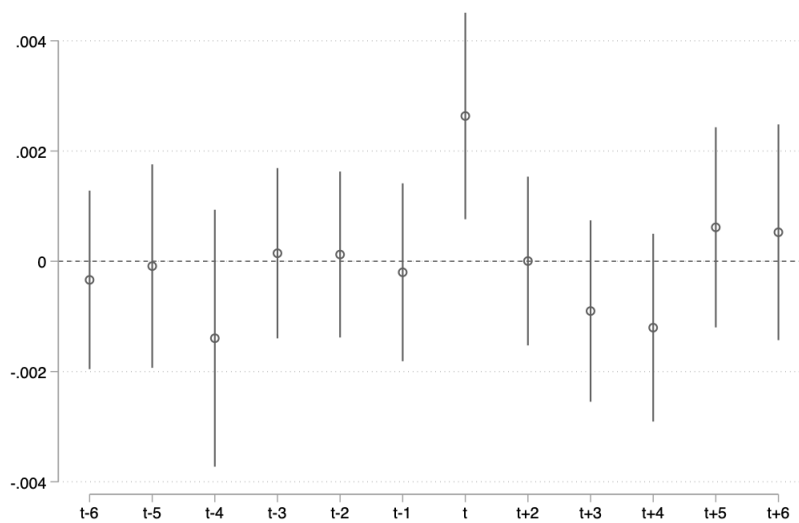
A Appendix Figures and Tables

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

Fatal Crashes (Rate per Million Population)



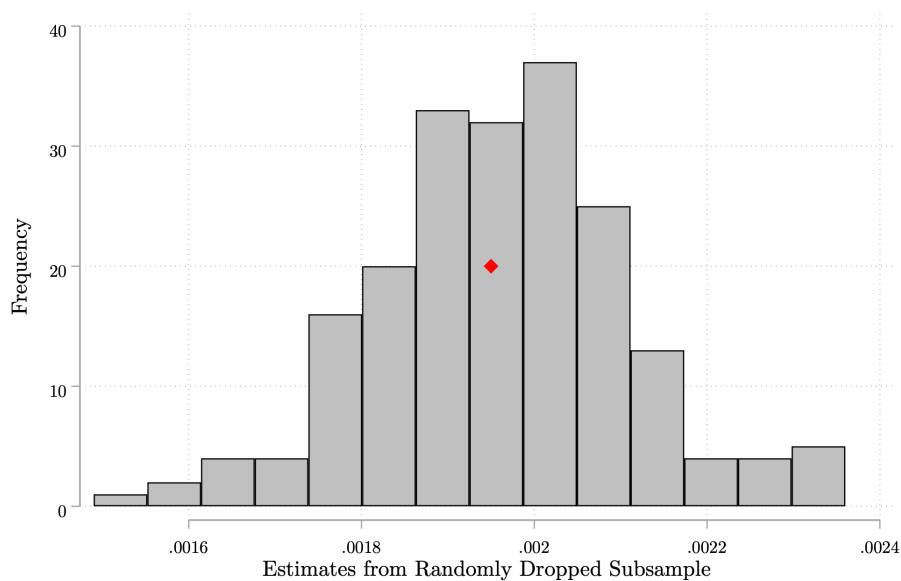
Fatalities (Rate per Million Population)



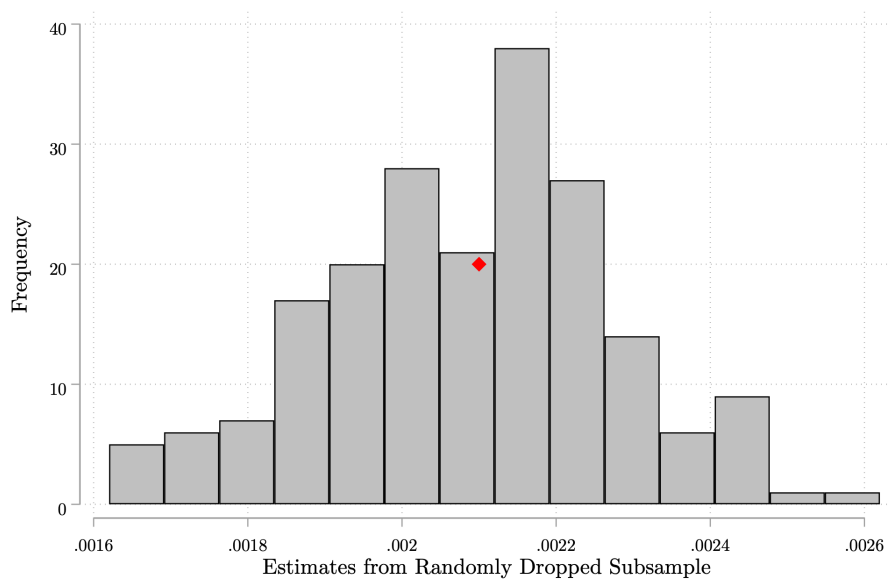
Note: Figure shows plotted coefficients from the estimation specified in Equation 3 with additional lags and leads of predicted particulate matter exposure for each day over the previous and subsequent week included.

Figure A.2: Distribution of Estimated Effects with Randomly Dropped Subsample

Fatal Crashes (Rate per Million Population)



Fatalities (Rate per Million Population)



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 the estimated coefficient from Table 2, Column 2 that includes all counties.

Table A.1: Alternative Temperature Specifications and Weather Interactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>First-stage</i>								
R^2	0.4583	0.4423	0.4716	0.4826	0.4468	0.4732	0.4590	0.4679
F	138,154	129,473	145,756	152,327	131,881	107,564	117,204	121,499
<i>Second-stage</i>								
Main specification	0.0020*** (0.0007)							
Binned avg. temp.		0.0023*** (0.0006)						
Finer high temp. bins			0.0015** (0.0007)					
Temperature deciles				0.0003 (0.0007)				
Sager (2019) temp. bins					0.0012* (0.0006)			
Cubic spline						0.0003 (0.0007)		
Linear avg. temp							0.0004 (0.0007)	
Quadratic avg. temp.								0.0004 (0.0007)
% Effect	0.86	1.00	0.66	0.15	0.51	0.13	0.20	0.17
County-by-Month-Year FE	X	X	X	X	X	X	X	X
Day-of-week FE	X	X	X	X	X	X	X	X
Alcohol/marijuana laws	X	X	X	X	X	X	X	X
Original temperature bins	X	X						
Finer high temperature bins			X					
Temperature deciles				X				
Sager (2019) temperature bins					X			
Temp bin x precip x wind speed FE	X	X	X	X				
Precip x wind speed FE					X	X	X	X

Note: Results from variations of the estimation specified in Equation 3. Outcome variable is the rate of fatal crashes per million population 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. Column 1 presents our baseline weather specification: fixed effects for two maximum temperature bins (below freezing and above 85-degrees Fahrenheit) interacted with precipitation deciles and wind speed deciles. Column 2 uses the average temperature instead of the maximum temperature to construct the two temperature variables. Column 3 uses the maximum temperature and 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 bins temperature into deciles and interacts them with the precipitation and wind speed deciles. Column 5 uses similar temperature bins as Sager (2019); approximately 10-degree Fahrenheit bins instead of 5-degree Celsius bins. Column 6 uses the cubic spline of the maximum temperature. Columns 7 and 8 use average temperature as a continuous variable linearly (7) and in quadratic form (8). 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: Effect on Traffic Stops Using All Available States

	Moving Violations	Warnings	Citations	Arrests	All Stops
	(1)	(2)	(3)	(4)	(5)
Effect Size	-0.4134** (0.1778)	-0.1666 (0.2291)	0.0797 (0.0937)	-0.0065 (0.0139)	-0.3795 (0.2696)
Mean of Outcome	97.5185	55.9916	48.2051	7.0518	196.7632
% Effect	-0.42	-0.30	0.17	-0.09	-0.19
<i>N</i>	364,022	303,984	313,022	218,103	364,022
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 sample includes traffic stop data from the following states: Arizona, California, Colorado, Florida, Georgia, Iowa, Michigan, Mississippi, Montana, North Carolina, North Dakota, New Hampshire, New York, South Dakota, Tennessee, Texas, Washington, and Wisconsin. The number of observations differs across columns as not every state records every type of stop outcome (warnings, citations, and arrests). The column header denotes the traffic-stop-related outcome. All effects represent stops or stop outcomes per million population. 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 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 all stops that result in a warning. Column 3 estimates the effect on all stops that result in a citation. Column 4 estimates the effect on all stops that result in an arrest. Column 5 estimates the effect on all stops. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.