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

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Abstract

There is mounting causal evidence that 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 speed and direction, we show that higher $PM_{2.5}$ exposure results in more fatal car crashes and fatalities. Further, it is only exposure within the preceding 24 hours that increases accidents and fatalities, highlighting the immediate negative effects of high-pollution days. Reducing fine particulate matter pollution by one standard deviation across the board 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 speed and 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 taxing, particularly in general equilibrium. There is a big cognitive difference between driving well in partial equilibrium (e.g., staying in one's lane, driving the speed limit, following posted signs, and using one's turn signal) and driving well in general equilibrium (anticipating other drivers swerving into your lane, paying enough attention to notice when a driver from a different direction is running a red light, or avoiding that one person cutting across five lanes of traffic to exit when you are also trying to merge to the right). The former relies on the parts of the brain that deal with routine and automated tasks. The latter relies on parts of the brain that deal with more complex tasks, like reaction time, rational thought, emotional regulation, and heightened spatial awareness. 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). In the case of driving, cognitive impairment can lead to detrimental outcomes for both the driver and those they impact.

Driving under impairment is well studied, and a robust literature exists that studies policies that affect drunk driving. This literature effectively examines the impact of reduced cognition for a subset of drivers. Prior research in this field has studied, among other policies, 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 such as Uber and Lyft (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. In other words, while the precise shape of the demand curve for drunk driving is not well known, we know that the demand curve generally slopes down.

A smaller but related literature studies the myriad effects of policies aimed at reducing crash risk for society's newest drivers (Deza and Litwok, 2016; Huh and Reif, 2021). These papers find that 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. This conforms with brain imaging research on teenage brains and development of the prefrontal cortex which show peaks and troughs of development, leading to changes in cognition, emotion, and behavior (Giedd, 2008); and with specific applications to teen brain development and self-regulation over behavior and emotions and its relevance to driving risks among youth (Dahl, 2008). For both populations, prior studies on policy changes can be considered as conditional outcomes on specific populations. That is, conditional on drivers choosing to drive under the influence (or conditional on the age 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.

We examine the effect of fine particulate matter exposure, which can affect both alcohol and non-alcohol-related crashes, the latter of which comprise the majority of fatal incidents.[1] Moreover, the cognitive shock we study also affects pedestrians and bicyclists who face the external cost of impaired drivers most severely. 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 likelihood of crashes.[2] Conversely, if cognition could be improved by improving environmental conditions across the board, our estimates imply that nearly 2,000 motor vehicle fatalities could be avoided yearly. We quantify the effect of reducing negative cognitive shocks to conservatively be worth $14.5 billion dollars per year.

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. Reviews of this literature include Anderson et al. (2012), Thangavel et al. (2022), and Cory-Slechta et al. (2023). Prominent effects caused by small particulates are oxidative stress and neuro-inflammation, which are seen in both humans and animals, and are supported by in-vitro studies (Costa et al., 2020). 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. Fine particles are harmful to brains because they are small enough to cross the blood-brain barrier and reduce oxygen to the brain. This affects both the central nervous system and brain health. Hahad et al. (2020) discuss an increased risk of cerebrovascular and neuropsychiatric disorders due to small particulates, showing that exposure contributes to cognitive dysfunction, neurodevelopmental disorders, emotional responses such as depression,

[1] In 2020, 30% of motor vehicle fatalities were due to alcohol-impaired driving (Stewart, 2022).

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

increased risk of stroke, dementia, and Parkinson's disease. Exposure to small particulates also negatively effects episodic memory (Ailshire and Crimmins, 2014).

While the precise molecular mechanisms of susceptibility remain largely unknown, recent findings indicate that inflammation and oxidative stress play significant roles in air pollution-induced disorders which can happen from both contemporaneous and prolonged exposure. This is believed to be influenced by the increased production of proinflammatory mediators and reactive oxygen (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 for the elderly (Deryugina et al., 2019) and on external causes whose negative externalities (e.g., suicide contagion) are indirect and not as immediate as those arising from motor vehicle crashes (Persico and Marcotte, 2022). Beyond these very dire and consequential outcomes, particulate matter pollution has also been linked to hampered real-time decision making and errors for professional chess players and umpires for Major League Baseball (Archsmith et al., 2018; Künn et al., 2019). This work highlights how pollution exposure results in real-time errors in decision-making among career experts in their fields, albeit in a lower-stakes environment than driving, where both rash decisions or small errors can result in fatal outcomes for drivers and those they share the road with.

Particulate matter pollution has also been linked to worse results in several other longer-term outcomes. Indeed, researchers and policymakers alike are interested in the direct effects of hampered cognition and the negative externalities from a society where everybody has

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

lower levels of cognition. For example, a consistent finding on particulate exposure and human capital development is that higher pollution concentration days lead to worse education outcomes (Komisarow and Pakhtigian, 2022; Persico and Venator, 2019; Pham and Roach, 2023). The proposed mechanism is that particulate matter pollution impacts the overall learning environment within schools because poor air quality can lead to decreased motivation and compromised concentration and error-making by students and teachers, which ultimately undermines the quality of teaching and learning experiences.

The causal link between high pollution concentrations and cognitive errors can also be seen in research showing that criminal activity and aggression increases with high particulate matter levels (Bondy et al., 2020; Burkhardt et al., 2019; Herrnstadt et al., 2021; Jones, 2022). Bondy et al. (2020) show that the particulate exposure at pollution levels that are well below current regulatory standards drives more crime, and further that the effect, "appears to be unevenly distributed across income groups" (Bondy et al., 2020). The former finding is supported by Pham and Roach (2023), who show that education outcomes deteriorate at levels lower than the current U.S. ambient standard. Further harms from particulate matter pollution include documented earnings losses (Borgschulte et al., 2022). These authors link satellite smoke plumes with labor market outcomes and find that an additional day of smoke exposure reduces quarterly earnings by about 0.1 percent, an effect driven in part by labor force exits and reduced employment.

The paper most closely related to ours, Sager (2019), also 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. For example, 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.

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. And while our instrument (wind speed and direction) is not perfect, because very high winds can affect driving ability, the first-stage regression predicting pollution concentrations using wind speed and direction has a negative coefficient for wind speed, meaning more wind predicts less pollution. We find more predicted pollution means more fatal car crashes, making the issue with the wind instrument one of attenuation bias. Therefore, our estimates can be considered a lower bound of the effect of pollution on 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 that 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.

In this paper, we find robust and consistent evidence that particulate matter exposure leads to more driving fatalities. Our identification strategy follows the standard instrumental variables method that many others have used, which takes advantage of exogenous changes in wind speed and 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 disparities between white and black particulate matter exposure. Particulate matter pollution is a by-product of the combustion of fuels from sources such as wildfires, power plants, and cars. These are measured in microns per cubic meter. 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. Moreover, prior work has shown that these small particulates can travel great distances and are not confined to their area of origin (Burke et al., 2021; Fowlie et al., 2019; Zou, 2021).

Figure **??** shows how annual average particulate matter concentrations have changed over time, and how much geographic variation there is across the United States using annual summary data available from Van Donkelaar et al. (2016).[4] The top portion of this figure shows annual averages at a tenth of a degree resolution for 2004, the year prior to the court-ordered enforcement of the 1990 update to the Clean Air Act (and the year prior to the start of our sample). The bottom portion shows annual averages at the same resolution in 2019, the last year in our sample. This figure shows how average annual $PM_{2.5}$ concentrations have fallen across the nation in recent years, resulting in much less geographic variation in fine particulate matter pollution at the annual level. Nevertheless, day-to-day variation can still peak at thresholds well above the EPA's regulation of 9 microns per cubic meter.

For these reasons, our use of wind direction and wind speed helps to alleviate multiple issues of measurement error that would bias our results. One 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

[4]Portions of Canada and Mexico are also shown in this figure, though we only use data from the United States in our models below.

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. Another reason to use instrumental variables is that tail-pipe emissions include small particulates, and so it is not unreasonable to expect counties or days with more driving to have elevated particulate matter readings. In addition, more cars on the road mean more accidents through a scale effect alone (not to mention through congestion externalities), which would bias our estimates upward. These offsetting sources of measurement error mean the effect of measurement error on our estimates is *a priori* uncertain. By using wind-speed and 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 find that a one-unit increase in mean particulate matter exposure is associated with 0.94% more fatal crashes on any given day, relative to the mean. Our finding that fatal crashes increase by 0.94% is larger than non-IV estimates would imply, suggesting that the attenuating measurement error effect of fixed monitor locations dominates the simultaneous determination effect. This effect size is persistent across modeling strategies, the inclusion of controls, using satellite versus monitor-based data, and even reinterpreting the outcome variable from count data into another form. For all main results we estimate weighted OLS instrumental variables models, but as an additional check we recast the dependent variable from the count of instances to a dichotomous indicator of whether or not a crash occurred, measured as a rate per hundred thousand people, or use a Poisson or inverse hyperbolic sine transformation to account for the many days with zero occurrences. All models yield similar conclusions. 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. In fact, our estimated effect size is nearly 12-times larger than the mean of results across this randomized falsification exercise. 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. In all iterations of this latter robustness check our results remain statistically significant.

In addition to data on the reading of particulate matter registered at a particular monitor, the EPA also calculates an Air Quality Index (AQI) value for particulate matter at each monitor that focuses on health effects that may be experienced within a few hours or days after breathing polluted air.[5] The AQI is a unitless measure of the amount of pollutant that can be used to relate the pollutant to healthy levels and indicate possible health concerns with elevated levels. AQI readings range from 0-500 with values above 151 marked as unhealthy, values between 201-300 very unhealthy, and readings above 301 are deemed hazardous. We also estimate all models using this metric of particulate matter pollution. Using this measure of particulate matter exposure, we see that a unit increase in $PM_{2.5}$ AQI is associated with a 0.25% increase in crashes.[6]

We also measure how traffic fatalities respond to differences in particulate matter pollution. If pollution affects decision-making by making drivers more aggressive, the severity of crashes may increase in addition to the number of fatal crashes. As there can be multiple fatalities per crash, fatalities may increase more than the increase in fatal crashes would suggest. Alternatively, if pollution affects decision processes by making drivers more error prone, that may lead to more single-fatality crashes, corresponding to a 1-for-1 increase in fatalities. We find that a one-unit increase in mean particulate matter concentration is associated with a 0.85% increase in traffic fatalities. Or put differently, a one standard deviation increase in $PM_{2.5}$ corresponds to a 5.39% increase in motor vehicle fatalities. This effect size is very similar to the effect on fatal crashes, suggesting that an increase in single-fatality crashes is driving our results. Using AQI as our exposure measure we find that each one-unit increase

[5]The EPA also computes separate AQI values for other criteria pollutants: PM_{10}, ozone, carbon monoxide, sulfur dioxide, and nitrogen dioxide.

[6]Note that unit changes are not directly comparable between mean $PM_{2.5}$ readings and the AQI, so a one-unit increase in $PM_{2.5}$ would register as more than a one-unit increase in AQI.

in AQI is associated with an approximate 0.23% increase in fatalities. These findings are robust to the same alternative modeling specifications discussed with fatal crashes.

2 Empirical Strategy

2.1 Data Description

2.1.1 Pollution and Weather data

Data on mean particulate matter concentrations and Air Quality Index (AQI) are collected from the Environmental Protection Agency's daily summaries by monitor (Environmental Protection Agency, 2022). The number of monitors varies over time as more are added, but from 2010 onward the number of locations is consistent, with over 359,000 individual observations yearly spread over 20,000 separate sites. The downside of using observed values from monitor-based readings is that fewer counties are covered. Only about 20% of counties have coverage, and daily coverage is not guaranteed for each monitor.[7] However, these monitors are located in more populated areas, which make up much of the observed car crash data as we discuss below.[8] The average daily $PM_{2.5}$ concentration is 9.78 and the average AQI is 37.69, both of which correspond to a "good" level of air quality (Table 1). However, 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. For AQI, the average within-county

[7]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.

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

standard deviation is 17.7 with a maximum within-county standard deviation of 37.3.

In a robustness specification, 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 (Centers for Disease Control and Prevention, 2021). 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).[9,10] Moreover, we now swap the issue of potential measurement error from the monitor-based data with the potential for calibration error with the satellite-based modeled data. Comparing between the monitor-based data and the satellite-based data we find a root mean squared difference of 1.38 units and a correlation coefficient of 0.914 between the two data sources. All estimates using these data are consistent with the monitor-based data.[11]

We couple our particulate pollution information with wind speed and direction data from the North American Regional Reanalysis daily reanalysis data.[12] 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 which are 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 10-degree bins.

Our IV strategy makes use of both wind direction and wind speed 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

[9] This is the EPA's 'Downscaler Model' which has information on particulate matter concentrations by census tract and by county.

[10] 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.

[11] These estimates are shown in Columns 5 and 6 of Table 2, and in Table 5.

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

there is no polluting activity blowing from the water. This pollution-clearing wind will have a bigger effect as wind speeds coming from the waterfront increase. Alternatively, suppose that a neighboring county 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 both wind speed and wind direction allow us to control for the simultaneous determination issue – more cars result in more accidents and more cars result in more particulate pollution, but we are interested in determining if more pollution causes more accidents.

We also use temperature and precipitation data from the NARR reanalysis data. There is a meteorological relationship between temperature and wind speeds where, all else equal, higher temperatures result in lower wind speeds. For example, this is why wind turbines are more productive and produce more electricity overnight than in the heat of an afternoon. In our first-stage regressions we control for the interaction of maximum daily temperature deciles (measured in degrees Fahrenheit) by precipitation deciles (measured in inches) by wind speed deciles (measured in meters per second). In this stage we allow for a broad range of temperature differences so that we can take full advantage of the effect that exogenous weather conditions have on particulate matter concentrations. We use decile bins to allow for heterogeneity in how heat affects particulate matter so that we are not imposing a linear relationship between the two variables. In our second-stage regressions we control for temperature effects using dichotomous indicator variables for two different degree bin ranges. We control for days when the maximum temperature is below freezing to account for icy conditions, and control for 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 temperament and may contribute to feelings of anger that could also be associated with car collisions (Baylis, 2020; Colmer and Doleac, 2022). The rationale for controlling for broader temperature indicators in the first-stage and not in the second stage is that this exogenous variation is highly related to wind speed and hence particulate matter concentrations. Choosing to include temperature in a more flexible form after controlling for its effect in the first stage has the unintended effect of re-introducing variation in particulate matter concentrations by way of a proxy variable after just controlling for variation that is due to meteorological conditions. We also control for 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).

2.1.3 Control variables

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

2.2 Econometric Specification

We estimate both OLS and instrumental variables specifications, using Baum et al. (2010)

and Correia (2016). Our preferred specification is the IV model, as the OLS estimation suffers from potential bias due to measurement error and the simulataneous determination problem. We first estimate the following OLS equation:

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

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 control variables: indicators for the maximum temperature being below freezing or above 85° F, indicators for precipitation in deciles, the blood alcohol concentration limit for operating a motor vehicle, and indicators for whether medical and recreational marijuana laws have been implemented. δ_{cm}, δ_{my}, and δ_{dow} represent county-by-month, month-year, and day-of-week fixed effects. County-by-month fixed effects account for demographic characteristics, the unemployment rate, and other standard time-varying county-level control variables. 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.[13]

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 (only in the non-IV specifications) or changes in wind speed and 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 and behaviors.

[13]We have also considered aggregating by commuting zone. Commuting zones represent labor market areas, and are typically larger and may be 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 since there is better precision connecting to local pollution conditions.

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 and velocity, 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:

$$AP_{cymd} = \alpha + \beta \cdot windvel_{cymd} + \gamma_c \cdot winddir_{cymd} + \rho \cdot W_{cymd} + \delta_{cm} + \delta_{my} + \varepsilon_{cymd} \tag{2}$$

AP_{cymd} denotes the air pollution measure for county c on day d in month m and year y. $windvel_{cymd}$ represents the wind velocity measurement. $\gamma_c \cdot winddir_{cymd}$ represents county fixed effects interacted with indicators for wind direction (split into 10-degree bins). W_{cymd} represents our weather variables: maximum daily temperature deciles interacted with precipitation deciles and wind speed deciles. δ_{cm} and δ_{my} denote county-by-month and month-year fixed effects. 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:

$$F_{cymd} = \alpha + \beta \cdot \widehat{AP}_{cymd} + \mathbf{X'_{cymd}} \cdot \theta + \delta_{cm} + \delta_{my} + \delta_{dow} \tag{3}$$

$\widehat{AP}_{cymd}$ is the predicted measure of air pollution from Equation 2. The controls for temperature are indicators for the maximum temperature being below freezing or above 85° F. All other variables are the same as those described in Equation 1.

3 Results

3.1 OLS

Our OLS results are in Panel A of Table 2. The results in Columns 1 and 2 use the $PM_{2.5}$ concentration as the measure of air pollution, while those in Columns 3 and 4 use the air quality index (AQI) for $PM_{2.5}$. Columns 1 and 3 include fixed effects but no time-varying controls. A one $\mu g/m^3$ 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 $\mu g/m^3$ increase in $PM_{2.5}$ is associated with an increase of 0.0002 fatal crashes per day, which is not significant.

Using the air quality index as the measure of pollution yields similar results. In our fixed-effects-only specification (Column 3), a one-unit increase in AQI corresponds to a 0.0002 increase in daily fatal crashes. This effect is significant at the 1% level and represents an increase of 0.05%. The results are slightly smaller when we include time-varying controls (Column 4) and only marginally statistically 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 $\mu g/m^3$ increase in $PM_{2.5}$ leads to an increase of 0.0004 fatalities per day, which is not significant. A one-unit increase in the AQI (Column 4) leads to an increase of 0.0002 fatalities per day, which is statistically significant at the 5% level.

3.2 Instrumental Variables

Panel B of Table 2 shows the results from our instrumental variables specification. The F-statistic for the first-stage regression of $PM_{2.5}$ concentration and wind velocity is 245.08, and the F-statistic for the first-stage regression of the air quality index for $PM_{2.5}$ and wind velocity is 329.83, both well above the threshold for valid inference (Lee et al., 2022). Column

1 includes fixed effects but no time-varying controls. 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 results are slightly attenuated when we add in controls (Column 2, our preferred specification): a one μg/m^3 increase in the predicted PM$_{2.5}$ concentration leads to an increase of 0.0035 fatal crashes per day. This effect is again significant at the 1% level and represents a 0.94% increase. The results using PM$_{2.5}$ AQI as the measure of pollution are attenuated but qualitatively similar. The attenuation is not surprising given that the air quality index ranges from 0 to 500 with a value below 50 considered "good" air quality, while the corresponding PM$_{2.5}$ concentration for "good" air quality is 12 μg/m^3. A one-unit increase in AQI is much smaller than a 1-unit increase in PM$_{2.5}$. In the specification with only fixed effects, a one-unit increase in predicted AQI leads to an increase of 0.0011 fatal crashes per day, a 0.29% increase that is statistically significant at the 1% level (Column 3). The results are virtually identical when we include controls (Column 4): a 0.0009-crash increase (0.25%).

The results for fatalities mirror those for crashes, although effects are statistically significant at the 5% level instead of the 1% level. In the version with controls (Column 2), a one μg/m^3 increase in predicted PM$_{2.5}$ leads to a 0.85% increase in fatalities. For context, a one standard deviation increase in PM$_{2.5}$ corresponds to a 5.39% increase in motor vehicle fatalities. Using AQI as the measure of pollution yields a 0.23% increase in 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 Poisson specification. Column 4 transforms the outcome variable using the inverse hyperbolic sine. In Column 5, the OLS-IV regression results are unweighted.

We find that a one μg/m^3 increase in predicted $PM_{2.5}$ leads to a 0.24 percentage point increase in the probability of any crashes or fatalities, a 0.97% increase that is significant at the 1% level (Column 1). When expressed as a rate per 100,000 people (Column 2) we estimate a 1.53% and 1.37% increase for each outcome, respectively. All estimates for this model are statistically significant at the 1% level. When we estimate a Poisson specification, we find an increase of 0.0052 crashes or fatalities per day, a 1.41% and 1.32% increase relative to the mean. These effects are significant at the 1% and 5% level, respectively. 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 0.0028 crashes and 0.0029 fatalities (0.77% and 0.74%), which are both significant at the 1% level. The unweighted OLS-IV regressions (Column 5) yield slightly smaller effect sizes but slightly larger percent effects than the weighted OLS-IV regressions. A unit increase in $PM_{2.5}$ leads to an increase of 0.0016 crashes and 0.0015 fatalities per day. These effects are statistically significant at the 1% level and correspond to a 1.63% and 1.45% increase over the mean. Results using the AQI for $PM_{2.5}$ are qualitatively similar and statistically significant but attenuated, which is to be expected given the different scale of the pollution variable.

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 the air quality index. Higher AQI should correspond to a larger effect on crashes and fatalities. We create indicator variables for whether the daily AQI was between 26 and 50, 51 to 100, or above 100 (AQI of 25 or less is the omitted group) and re-estimate Equation 3 using these indicator variables instead of the level of AQI.[14] For these regressions, we use actual AQI, as opposed to our predicted AQI instrument, as predicted values of AQI are all

[14]We do not further parse the highest AQI bin due to a lack of statistical power: less than 1% of the sample records an AQI greater than 100, and less than 0.1% records an AQI greater than 150.

less than 50, providing insufficient variation. In our sample period, the majority of high-AQI days (101 or higher) occur due to wildfires. We exclude county-by-month fixed effects from this estimation because wildfires are concentrated in certain counties and months.[15] We replace them with county 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) 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 $PM_{2.5}$, as measured by AQI, correspond to more crashes and fatalities. On days where the air quality index is between 26 and 50, there are an additional 0.0081 crashes and 0.0076 fatalities relative to days where the AQI is 25 or less. These effects are significant at the 5% level. On days when the AQI is between 51 and 100 (moderate air quality), there are 0.0149 additional crashes and 0.0165 additional fatalities. These results are significant at the 1% level. On days when the AQI is above 100 (ranging from unhealthy for sensitive groups to hazardous), there are an additional 0.0320 crashes and 0.0282 fatalities. The former is not statistically significant and the latter is marginally significant. That these estimates are less precisely estimated is unsurprising given that very few counties in the U.S. have a daily average AQI above 100. 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 concen-

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

[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.

tration over the prior week. Exposure over the prior 24 hours increases both crashes and fatalities in a statistically meaningful way, but the effect of prior days' concentrations cannot be distinguished from zero. These results support the notion that immediate exposure levels matter, and that the mechanism behind our findings are increases in mistakes and higher aggression levels as prior research has shown.

As a falsification exercise, we 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. From the figure, it is clear that only contemporaneous particulate matter exposure affects fatal driving outcomes.

Our primary results focus on the period after the more stringent Clean Air Act standards were enforced (after April 2005), but as a robustness check we include data from earlier years in the appendix. There are fewer pollution monitors in these years, so for some counties we are able to add observations while for others we cannot. The results, in Table $A.1$, are identical to the third decimal place. When we instrument for pollution using wind direction and velocity, increases in $PM_{2.5}$ lead to additional car crashes and fatalities.

Our analysis primarily uses monitor-based pollution readings, though an alternative to this is to use satellite-informed modeled data. The benefit to these data is that they offer broader spatial coverage with no missing readings, but the downside is that we substitute potential measurement error with model calibration error and have a shorter time sample. Nevertheless, we re-estimate the same model specification shown in Columns 1 through 4 of Table 2 using the satellite-based PM2.5 readings and come to the same conclusions as before. Panel B, Column 6 of Table 2 shows that a 1-unit increase in PM2.5 is associated with a 1.45 and 1.40 percent increase in fatal crashes and fatalities, respectively. Table 5 estimates alternative functional form specifications using the satellite data (akin to Table 3's specifications using the EPA monitor data), and shows results that are quantitatively very similar to both the satellite results in Panel B, Column 6 of Table 2 and to the functional form specification checks using the EPA monitor data in Table 3.

Lastly, we run two randomized falsification exercises to determine if variation in particulate matter is truly what is driving our result that both crashes and fatalities increase with higher pollution levels. For the first test we impose random matching to connect the data on 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 which is part of the DFW metroplex. We repeat this random matching exercise 250 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 driven by chance or model-driven bias. The mean effect size among the randomized matches is 0.00019 for crashes, and 0.00022 for fatalities, approximately 12 times smaller than the non-randomized estimate.[18] For the fatal crashes randomization, three out of the 250 replications (1.2%) yield an estimated effect size larger than our estimate, but they are not statistically significant. Next, we test whether or not 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 in Broderick et al. (2021). Broderick et al. (2021) have shown that sensitivity of

[17] A total of 500 random matches across both outcome variables.

[18] We also compute an average z-statistic of approximately 0.51 and 0.55 for these variables, respectively.

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 250 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 clearly shows that our estimates are not sensitive to removing observations from the sample. For crashes, we find that the mean effect size across iterations is 0.00236.[19] In fact, all of the 250 iterations are statistically significant at at least the 10% level. For fatalities, we find that the mean effect size across iterations is 0.00235.[20] These are similarly all statistically significant at the 10% level or more. We conclude from these randomization tests that our result is not due to model-induced bias, nor is it sensitive to removing particular counties.

4 Conclusions and Policy Discussion

Particulate matter pollution has been linked to numerous negative health outcomes, and importantly, has also been linked to decreased cognitive function, increased errors in decision-making, and reductions in pro-social behavior. In this paper, we focus on motor vehicle crashes and fatalities as these are a channel through which deteriorated cognitive and aggressive effects could play a very harmful role. We find robust evidence that particulate matter pollution leads to increases in fatal crashes and fatalities. To identify causal effects of pollution on fatal motor vehicle incidents, we make use of exogenous shifts in wind direction and velocity 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

[19] We find a mean z-statistic of 2.89.
[20] We find a mean z-statistic of 2.5.

exposure. We find that contemporaneous exposure over the prior 24 hours increases both motor vehicle crashes and fatalities, and do not find that pollution exposure over the prior week has any effect on fatal motor vehicle incidents. Further, the effect of air pollution is nonlinear, as higher levels of $PM_{2.5}$ (as measured by AQI) lead to greater increases in crashes and fatalities. These results support the hypothesis that the mechanism driving our results is real-time cognitive effects of particulate matter pollution.

Crashes and fatalities pose both significant economic costs to 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 both more crashes and more fatalities. When we translate our results into fatalities per hundred thousand people, we find that a 10 $\mu g/m^3$ increase in daily mean $PM_{2.5}$ concentration 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.[21]

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 5.39% increase in motor vehicle fatalities. Consequently, an across-the-board 1 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 $14.5 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.

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

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5 Tables

Table 1: Summary Statistics

	(1)
PM2.5 Concentration (μ/m^3)	9.7765
	(6.3378)
Air Quality Index	37.6949
	(18.8550)
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)	EPA AQI (3)	EPA AQI (4)	CDC $PM_{2.5}$ (5)	CDC $PM_{2.5}$ (6)
Panel A: OLS Results						
Fatal Crashes	0.0004*	0.0002	0.0002***	0.0001*	0.0005**	0.0003
	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0003)	(0.0002)
Mean of Crashes	0.3688	0.3688	0.3699	0.3699	0.2844	0.2844
% Effect	0.12	0.07	0.05	0.04	0.18	0.10
N	1,801,586	1,801,586	1,787,163	1,787,163	3,334,786	3,334,786
Fatalities	0.0006**	0.0004	0.0002***	0.0002**	0.0007*	0.0005
	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0003)	(0.0003)
Mean of Fatalities	0.3951	0.3951	0.3963	0.3963	0.3060	0.3060
% Effect	0.14	0.10	0.06	0.05	0.21	0.15
N	1,801,586	1,801,586	1,787,163	1,787,163	3,334,786	3,334,786
Panel B: Instrumental Variables Results						
Fatal Crashes	0.0040***	0.0035***	0.0011***	0.0009***	0.0045***	0.0041***
	(0.0013)	(0.0012)	(0.0004)	(0.0003)	(0.0015)	(0.0013)
Mean of Crashes	0.3688	0.3688	0.3699	0.3699	0.2844	0.2844
% Effect	1.09	0.94	0.29	0.25	1.59	1.45
N	1,801,586	1,801,586	1,787,163	1,787,163	3,334,786	3,333,495
Fatalities	0.0039**	0.0034**	0.0010**	0.0009**	0.0046***	0.0043***
	(0.0016)	(0.0015)	(0.0004)	(0.0004)	(0.0016)	(0.0014)
Mean of Fatalities	0.3951	0.3951	0.3963	0.3963	0.3060	0.3060
% Effect	0.98	0.85	0.26	0.23	1.52	1.40
N	1,801,586	1,801,586	1,787,163	1,787,163	3,334,786	3,333,495
County FE						
County-by-Month FE	X	X	X	X	X	X
Month-Year FE	X	X	X	X	X	X
Day-of-week FE	X	X	X	X	X	X
Weather		X		X		X
Demographics						
Alcohol/marijuana laws		X		X		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 245.08 for predicted $PM_{2.5}$ using the EPA monitor data (Panel B, Columns 1-2), 329.83 for predicted AQI using the EPA monitor data (Panel B, Columns 3-4), and 398.63 for predicted $PM_{2.5}$ using the CDC satellite data (Panel B, Columns 5-6). Outcome variables are from the Fatality Analysis Reporting System and pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019 (Columns 1-4) or the Centers for Disease Control for 2005-2016 (Columns 5-6). Other control variables are indicators for the daily high temperature below freezing, the daily high temperature above 85 degrees Fahrenheit, precipitation deciles, BAC limit, and legality of medical and recreational marijuana. There are also county-by-month, 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 Using EPA Monitor Pollution Data

	LPM (1)	Rate (2)	Poisson (3)	IHS (4)	Unweighted (5)
Fatal Crashes: $PM_{2.5}$	0.0024***	0.0003***	0.0052***	0.0028***	0.0016***
	(0.0008)	(0.0001)	(0.0020)	(0.0009)	(0.0004)
Mean of Crashes	0.2500	0.0227	0.3688	0.3688	0.0990
% Effect	0.97	1.53	1.41	0.77	1.63
N	1,801,586	1,801,586	1,115,019	1,801,586	1,801,586
Fatal Crashes: AQI	0.0006***	0.0001***	0.0014***	0.0008***	0.0004***
	(0.0002)	(0.0000)	(0.0005)	(0.0002)	(0.0001)
Mean of Crashes	0.2506	0.0227	0.3699	0.3699	0.0994
% Effect	0.26	0.41	0.38	0.21	0.43
N	1,787,163	1,787,163	1,103,467	1,787,163	1,787,163
Fatalities: $PM_{2.5}$	0.0024***	0.0003***	0.0052**	0.0029***	0.0015***
	(0.0008)	(0.0001)	(0.0022)	(0.0010)	(0.0004)
Mean of Fatalities	0.2500	0.0244	0.3951	0.3951	0.1067
% Effect	0.97	1.37	1.32	0.74	1.45
N	1,801,586	1,801,586	1,115,019	1,801,586	1,801,586
Fatalities: AQI	0.0006***	0.0001***	0.0014**	0.0008***	0.0004***
	(0.0002)	(0.0000)	(0.0006)	(0.0003)	(0.0001)
Mean of Fatalities	0.2506	0.0244	0.3963	0.3963	0.1071
% Effect	0.26	0.37	0.35	0.20	0.39
N	1,787,163	1,787,163	1,103,467	1,787,163	1,787,163
County FE					
County-by-Month FE	X	X	X	X	X
Month-Year FE	X	X	X	X	X
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 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 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. 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 indicators for the daily high temperature below freezing, the daily high temperature above 85 degrees Fahrenheit, precipitation deciles, BAC limit, and legality of medical and recreational marijuana. There are also county-by-month, 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 AQI

	Crashes (1)	Fatalities (2)
AQI 26-50	0.0081**	0.0076**
	(0.0031)	(0.0037)
AQI 51-100	0.0149***	0.0165***
	(0.0048)	(0.0061)
AQI 101+	0.0320	0.0282*
	(0.0219)	(0.0165)
Dependent Variable Mean	0.3699	0.3963
N	1,786,594	1,786,594
County FE	X	X
County-by-Month FE		
Month-Year FE	X	X
Day-of-week FE	X	X
Weather	X	X
Demographics	X	X
Alcohol/marijuana laws	X	X

Note: Results from a variation of the estimation specified in Equation 3. The measures of pollution are indicators for whether the air quality index was 26 to 50 (good), 51 to 100 (moderate), or higher than 100 (unhealthy). The omitted group is an indicator for the air quality index being 25 or less. 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 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 are indicators for the daily high temperature below freezing, the daily high temperature above 85 degrees Fahrenheit, precipitation deciles, the monthly unemployment rate, BAC limit, and legality of medical and recreational marijuana. There are also county, 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 5: Robustness Checks: Functional Form Specification Using CDC Satellite Pollution Data

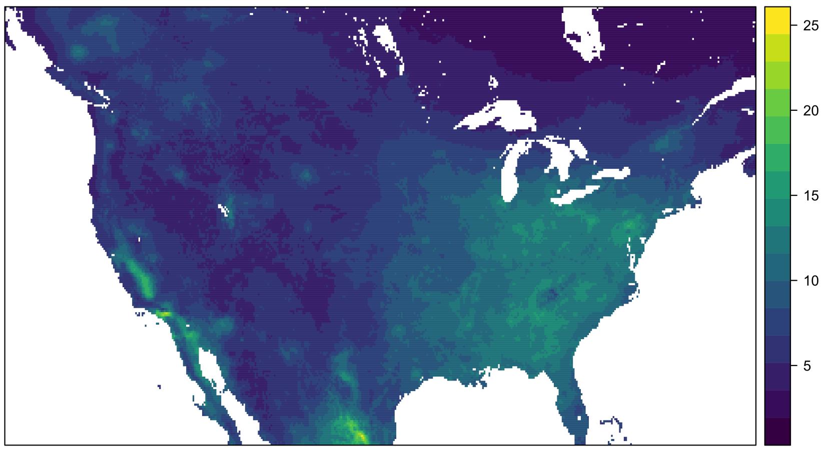
	LPM	Rate	Poisson	IHS	Unweighted
	(1)	(2)	(3)	(4)	(5)
Fatal Crashes: $PM_{2.5}$	0.0024***	0.0004***	0.0059***	0.0030***	0.0014***
	(0.0007)	(0.0001)	(0.0019)	(0.0009)	(0.0003)
Mean of Crashes	0.2021	0.0243	0.2844	0.2844	0.0715
% Effect	1.19	1.71	2.06	1.06	1.95
N	3,334,786	3,334,786	2,147,434	3,334,786	3,334,786
Fatalities: $PM_{2.5}$	0.0024***	0.0004***	0.0062***	0.0031***	0.0014***
	(0.0007)	(0.0001)	(0.0018)	(0.0009)	(0.0003)
Mean of Fatalities	0.2021	0.0264	0.3060	0.3060	0.0776
% Effect	1.19	1.63	2.03	1.01	1.85
N	3,334,786	3,334,786	2,147,434	3,334,786	3,334,786
County FE					
County-by-Month FE	X	X	X	X	X
Month-Year FE	X	X	X	X	X
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 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 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. Outcome variables are from the Fatality Analysis Reporting System and satellite pollution data are from the Centers for Disease Control for 2005-2016. Other control variables are indicators for the daily high temperature below freezing, the daily high temperature above 85 degrees Fahrenheit, precipitation deciles, BAC limit, and legality of medical and recreational marijuana. There are also county-by-month, month-year, and day-of-week fixed effects. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

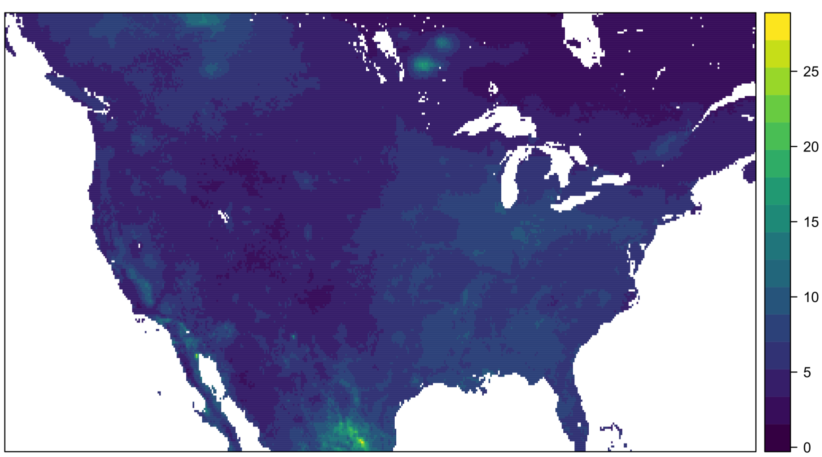
6 Figures

Figure 1: Pollution Variation Over Time and Geography

Average Annual PM2.5 Concentrations in 2004



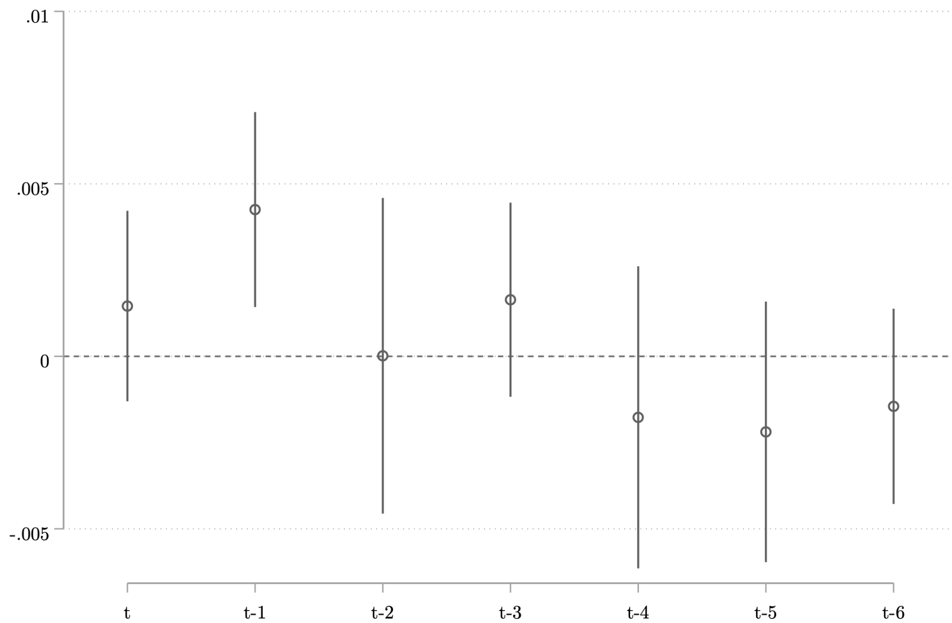
Average Annual PM2.5 Concentrations in 2019



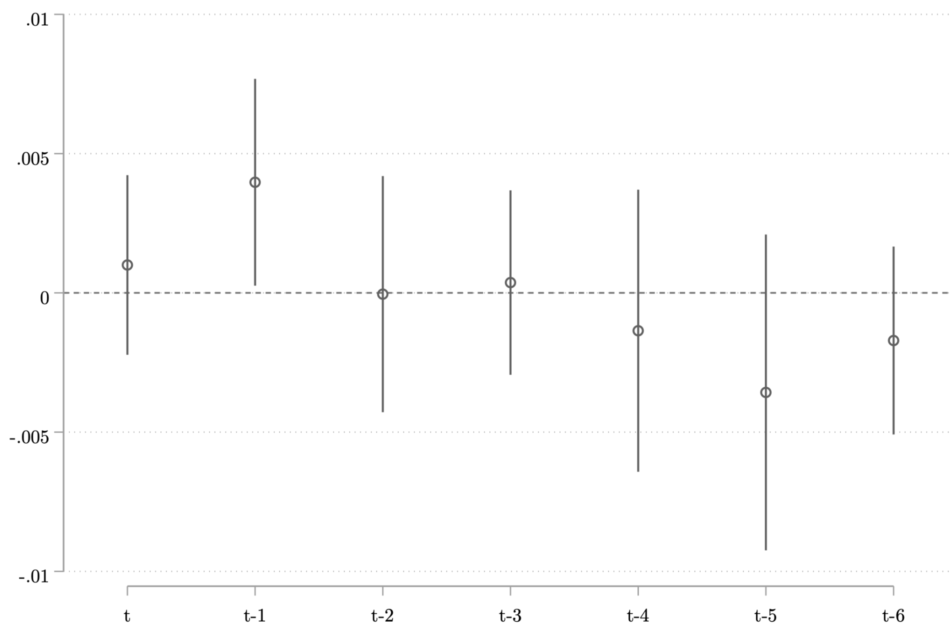
Note: Figures show average annual PM2.5 concentrations for North America at a tenth of a degree resolution for two sample years, 2004 and 2019. Color scale on right-hand axis shows concentration values in $\mu g/m^3$ units.

Figure 2: Lagged Particulate Matter Exposure

Number of Fatal Crashes



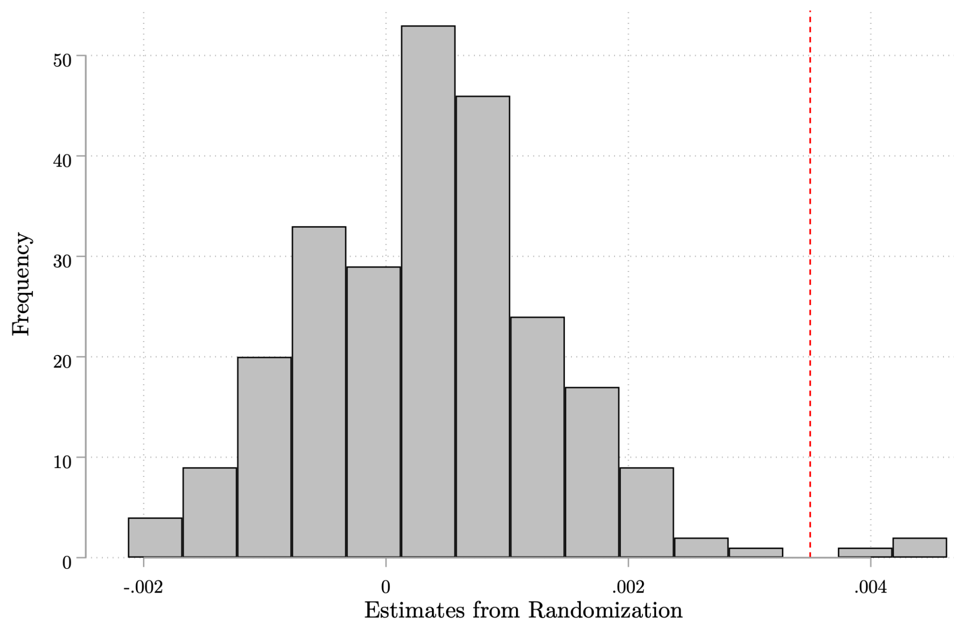
Number of Fatalities



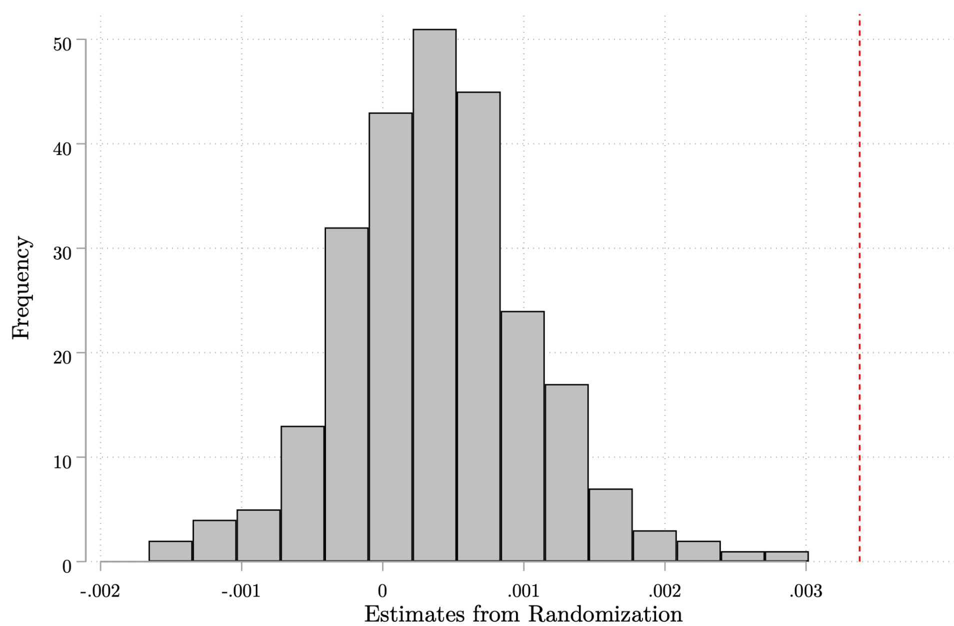
Note: Figure shows plotted coefficients from the estimation specified in Equation 3 with additional lags of particulate matter exposure included.

Figure 3: Randomization Tests

Number of Fatal Crashes



Number of Fatalities

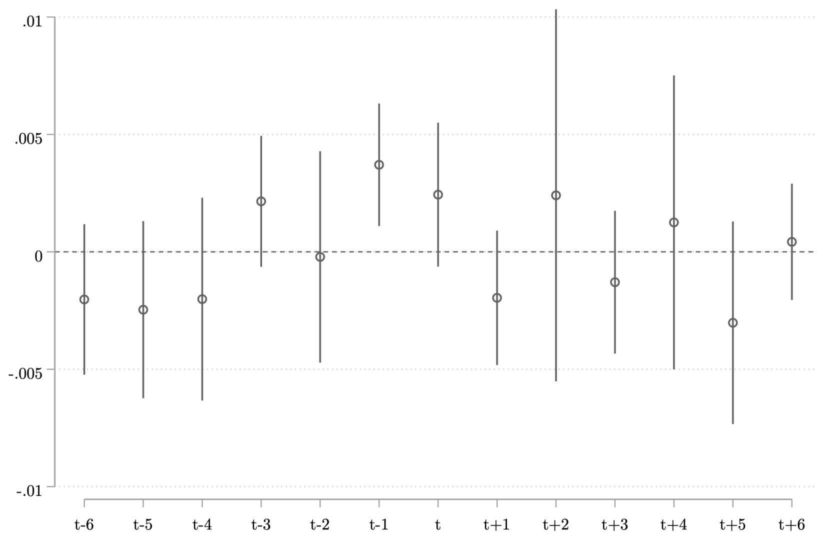


Note: Histogram plots the frequency of estimated coefficients for 250 replications of a randomization exercise in which observations for the dependent variable are randomly matched with particulate matter exposure and controls from another county. The red line plots the estimated coefficient without randomization from the estimation specified in Equation 3 shown in Table 2.

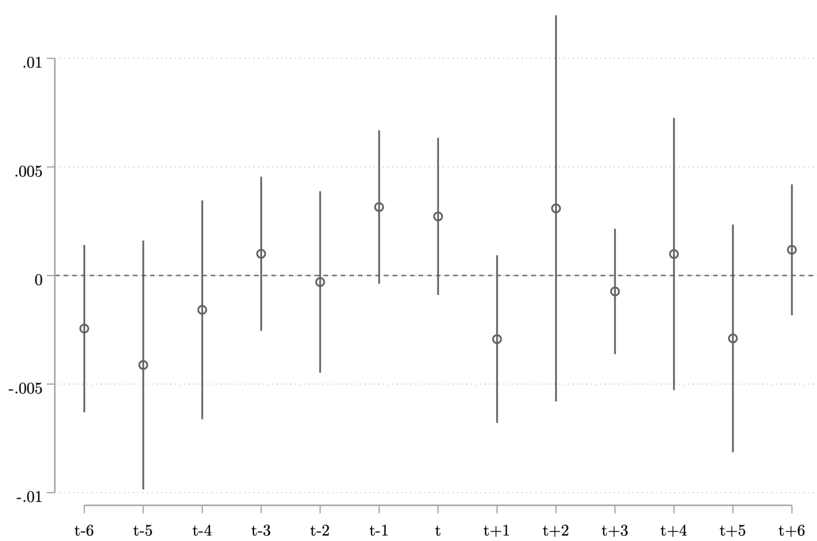
A Appendix Figures and Tables

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

Number of Fatal Crashes



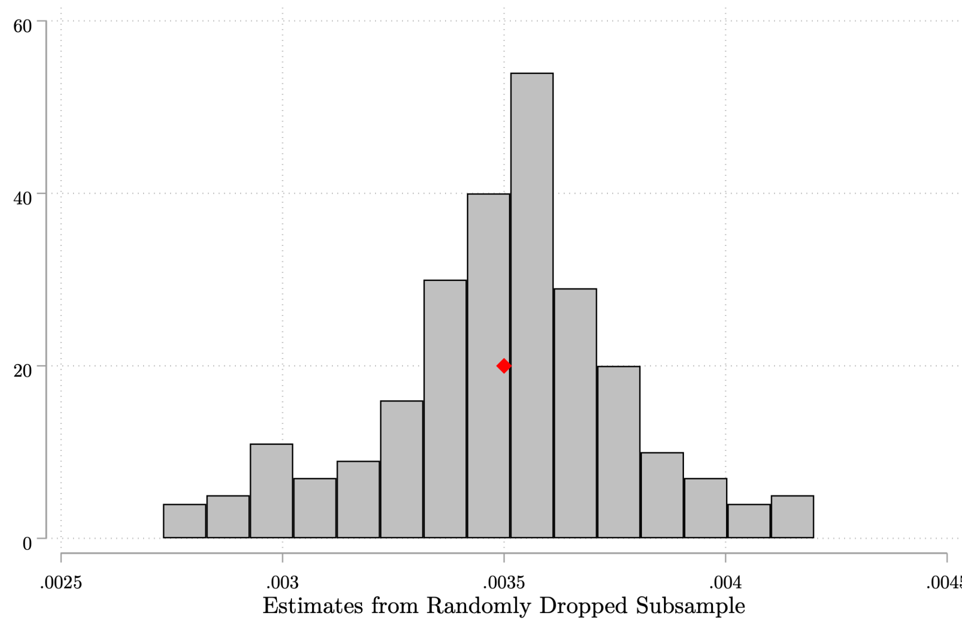
Number of Fatalities



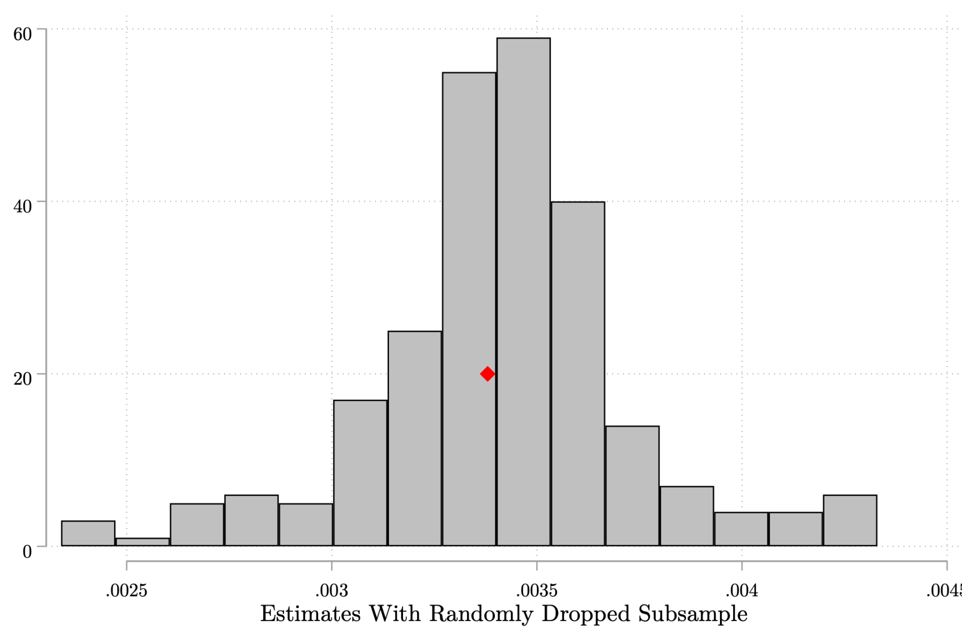
Note: Figure shows plotted coefficients from the estimation specified in Equation 3 with additional lags and leads of particulate matter exposure included.

Figure A.2: Coefficient Distribution with Randomly Dropped Subsample

Number of Fatal Crashes



Number of Fatalities



Note: Figure shows plotted coefficients from 250 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: The Effect of Air Pollution on Fatal Crashes and Fatalities, All Years

	$PM_{2.5}$ (1)	$PM_{2.5}$ (2)	AQI (3)	AQI (4)
Panel A: OLS Results				
Fatal Crashes	-0.0000	-0.0002	0.0001	-0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Mean of Crashes	0.3870	0.3870	0.3879	0.3879
% Effect	-0.00	-0.05	0.02	-0.00
N	2,367,802	2,367,802	2,353,379	2,353,379
Fatalities	0.0001	-0.0000	0.0001	0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Mean of Fatalities	0.4168	0.4168	0.4177	0.4177
% Effect	0.02	-0.01	0.02	0.01
N	2,367,802	2,367,802	2,353,379	2,353,379
Panel B: Instrumental Variables Results				
Fatal Crashes	0.0039***	0.0036***	0.0011***	0.0010***
	(0.0011)	(0.0010)	(0.0003)	(0.0003)
Mean of Crashes	0.3870	0.3870	0.3879	0.3879
% Effect	1.01	0.94	0.28	0.26
N	2,301,613	2,301,613	2,287,190	2,287,190
Fatalities	0.0036***	0.0033***	0.0010***	0.0009***
	(0.0012)	(0.0011)	(0.0003)	(0.0003)
Mean of Fatalities	0.4168	0.4168	0.4177	0.4177
% Effect	0.86	0.79	0.24	0.22
N	2,301,613	2,301,613	2,287,190	2,287,190
County FE				
County-by-Month FE	X	X	X	X
Month-Year FE	X	X	X	X
Day-of-week FE	X	X	X	X
Weather		X		X
Demographics				
Alcohol/marijuana laws		X		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. The F-statistic for the first-stage regression for predicted $PM_{2.5}$ is 273.49 and the F-statistic for the first-stage regression for predicted AQI is 379.43. Outcome variables are from the Fatality Analysis Reporting System for 1999-2019 and pollution data are from the Environmental Protection Agency Air Quality Data for 1999-2019. Other control variables are indicators for the daily high temperature below freezing, the daily high temperature above 85 degrees Fahrenheit, precipitation deciles, BAC limit, and legality of medical and recreational marijuana. There are also county-by-month, month-year, and day-of-week fixed effects. Standard errors are clustered at the county level and regressions are weighted by the county population. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.