Particulate Matter Pollution and Fatal Car Crashes*

Anne M. Burton† and Travis Roach‡

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Abstract

There is mounting causal evidence that particulate matter pollution reduces real-time cognitive function and increases aggressive behavior. We investigate a setting in which both of these functions matter greatly: 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 1,500 motor vehicle fatalities in 2019.

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†University of Texas at Dallas, anne.burton@utdallas.edu
‡University of Central Oklahoma, troach2@uco.edu.

1 Introduction and Background

The negative health and psychological effects of particulate matter pollution are well documented, beginning in utero with higher infant mortality and poor neonatal development,[1] and continuing later in life with poor long-run health, cognitive decline, and premature death.[2] Beyond these very consequential outcomes, particulate matter pollution has also been linked to hampered real-time decision making and errors (Archsmith et al.; 2018; Künn et al.; 2019; Persico and Venator; 2019), worse education outcomes (Komisarow and Pakhtigian; 2022; Pham and Roach; 2022), criminal activity and aggression (Bondy et al.; 2020; Burkhardt et al.; 2019; Herrnstadt et al.; 2021; Jones; 2022), and suicide (Persico and Marcotte; 2022). The biological mechanism behind these observed effects of particulate pollution is that small particulate matter is able to reduce the flow of oxygen into the bloodstream and brain. Additionally, this is associated with proinflammatory cytokines that are linked with depressive mood states (Persico and Marcotte; 2022). Through this growing literature, it is clear that particulate matter pollution is an important determinant of many short and long-term negative health effects. In this paper, we analyze how particulate pollution affects a largely preventable and leading cause of death for young people: fatal motor vehicle incidents.

Driving requires many different types of decision-making. Some decisions are routine like the route you choose or the speed you drive. Some others require immediate attention and are idiosyncratic, such as responding quickly to another driver that has suddenly entered your lane. Other risk factors for car crashes are traffic congestion, aggressive driving, and drug and alcohol use. All of these high and low stakes decisions could be impacted by environmental conditions like the amount of particulate matter pollution, which prior literature has shown is associated with both worse real-time decision-making and increased aggression. We study

[1] Currie and Walker (2011); Jones and Goodkind (2019); Jones (2020); DeCicca and Malak (2020)

[2] Muller and Mendelsohn (2007); Heutel and Ruhm (2016); Burnett et al. (2018);Deryugina et al. (2019); Tschofen et al. (2019); Anderson (2020); Choma et al. (2021); Hollingsworth et al. (2021); Wang et al. (2022)

how daily variation in particulate matter pollution affects the number of motor vehicle fatalities and fatal crashes and find a robust, persistent, and immediate effect of pollution on both outcomes.

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, and the EPA currently considers concentrations greater than 12 $\mu g/m^3$ to be harmful to human health. That said, it is not uncommon for concentrations to peak at much higher levels than this. 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).

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 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 approximately 0.7% more crashes on any given day, relative to the mean. Our finding that crashes increase by 0.7% is slightly 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, and even reinterpreting the outcome variable. For all main results we estimate weighted Poisson 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 the 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 robustness check our results remain statistically significant.

The EPA calculates an Air Quality Index (AQI) value for particulate matter that focuses on health effects that may be experienced within a few hours or days after breathing polluted air.[3] 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 AQI is associated with a 0.2% increase in crashes.[4]

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 an approximate 0.65% increase in traffic fatalities. Or put differently, a one standard deviation increase in $PM_{2.5}$ corresponds to a 4.2% 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 in AQI is associated with an approximate 0.19% increase in fatalities. These findings are robust to the same alternative modeling specifications discussed with fatal crashes.

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

[4] 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.

This paper contributes to several different literatures. First, we contribute to the growing literature on the health and mortality effects of fine particulate matter pollution (Anderson; 2020; Choma et al.; 2021; Currie and Walker; 2011; DeCicca and Malak; 2020; Deryugina et al.; 2019; Heutel and Ruhm; 2016; Hollingsworth et al.; 2021; Jones; 2020; Muller and Mendelsohn; 2007; Persico and Marcotte; 2022; Wang et al.; 2022). We show that in addition to the myriad health effects of air pollution, there are effects on mortality through increases in fatal motor vehicle crashes. Even in non-fatal crashes, a severe accident caused by heightened particulate matter levels may mean future chronic health issues or hospital visits. Within this literature, the most closely related paper to ours estimates the effect of air pollution on car crashes in the United Kingdom (Sager; 2019). Using temperature inversions as an exogenous source of variation in air pollution, they find that increases in air pollution correspond to increases in crashes. We find similar results studying a different geographic region (the United States) and using a different source of exogenous variation. We also contribute to the broader literature on the costs of pollution by studying the impact on fatal motor vehicle incidents (Archsmith et al.; 2018; Bondy et al.; 2020; Burkhardt et al.; 2019; Herrnstadt et al.; 2021; Jones; 2022; Komisarow and Pakhtigian; 2022; Künn et al.; 2019; Persico and Venator; 2019; Tschofen et al.; 2019).

Third, we contribute to the literature on determinants of fatal motor vehicle crashes by documenting an additional determinant of fatal crashes: air quality. Much of the work in this area focuses on policies or phenomena that target drunk driving, such as the Minimum Legal Drinking Age (Carpenter and Dobkin; 2017; Carpenter et al.; 2016), Blood Alcohol Concentration laws and associated punishments (Freeman; 2007; Hansen; 2015), restrictions on hours for alcohol sales (Green and Krehic; 2022; Lovenheim and Steefel; 2011), and ridesharing services such as Uber and Lyft (Burton; 2021; Dills and Mulholland; 2018). We examine a potential factor that could affect both alcohol and non-alcohol-related crashes, the latter of which comprise the majority of fatal incidents.[5]

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 monitors 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. However, these monitors are located in more populated areas, which make up much of the observed car crash data as we discuss below. 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 standard deviation is 17.7 with a maximum within-county standard deviation of 37.3.

We couple the particulate pollution information with wind speed and direction data from the North American Regional Reanalysis daily reanalysis data.[6] Wind conditions are

[5] In 2020, 30% of motor vehicle fatalities were due to alcohol-impaired driving (Stewart; 2022).
[6] These data are collected using the climateR package by Johnson (2022)

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 dichotomous indicator variables indicating whether or not the prevailing wind fell within three bin ranges: 0-90 degrees (North-Northeast), 90-180 (Southeast-South), and 180-270 (South-Southwest). The excluded reference bin is 270-360 (West-Northwest).

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 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 deciles of maximum daily temperature, measured in degrees Fahrenheit, and precipitation measured in inches. 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. Moreover, 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

We control for county-level demographic and economic characteristics as well as alcohol and marijuana policies. Annual county-level demographic characteristics come from the U.S. Census Bureau, and include population breakdowns by race, sex, and age (U.S. Census Bureau; 2022). For economic characteristics, we use the monthly unemployment rate from the Bureau of Labor Statistics (Bureau of Labor Statistics; 2022). 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 Poisson and instrumental variable specifications. Our preferred specification is a Poisson model, as our outcomes of interest are count variables that are heavily skewed towards 0: 75% of days have 0 crashes and 0 fatalities. We estimate the following Poisson equation:

$$\mathbb{E}[F_{cymd}|\ AP,\ \mathbf{X}] = exp\{\alpha + \beta \cdot AP_{cymd} + \mathbf{X}'_{\mathbf{cymd}} \cdot \theta + \gamma_c + \delta_{sm} + \delta_{my} + \delta_{dow}\} \tag{1}$$

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, indicators for whether medical and recreational marijuana laws have been implemented, the monthly unemployment rate, and annual demographic variables: 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 (omitted demographic categories are the fraction of the population that is white and the fraction of the population that is female and other ages). γ_c denotes county fixed effects and δ_{sm}, δ_{my}, and δ_{dow} represent state-by-month, month-year, and day-of-week fixed effects. 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.

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 would come primarily from weather events, such as wildfires 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.

Ordinary Poisson regressions of air pollution on fatal crashes may suffer from omitted variable 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:

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

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 four bins). W_{cymd} represents our weather variables: deciles of maximum daily temperature and precipitation. δ_{sm} and δ_{my} denote state-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 then estimate the second-stage effect of air pollution on fatal motor vehicle incidents using the following Poisson specification:

$$\mathbb{E}[F_{cymd}|\ AP,\ \mathbf{X}] = exp\{\alpha + \beta \cdot \widehat{AP}_{cymd} + \mathbf{X'_{cymd}} \cdot \theta + \gamma_c + \delta_{sm} + \delta_{my} + \delta_{dow}\} \tag{3}$$

$\widehat{AP}_{cymd}$ 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 Poisson

Our Poisson 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). Columns 1 and 3 include fixed effects but no time-varying controls. A one μg/m^3 increase in $PM_{2.5}$ is associated with a daily increase of 0.0003 fatal crashes. This effect is small and not statistically significant, representing a 0.11% increase over the mean. Including time-varying controls attenuates the estimate: a one μg/m^3 increase in $PM_{2.5}$ is associated with an increase of 0.0001 fatal crashes per day, which is not significant.

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 5% level and represents an increase of 0.06% relative to the mean. The results are slightly smaller when we include time-varying controls (Column 4) and no longer 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 μg/m^3 increase in $PM_{2.5}$ leads to an increase of 0.0002 fatalities per day, which is not significant. A one-unit increase in the AQI (Column 4) leads to an increase of 0.0001 fatalities per day, which is also not significant.

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 546.15, and the F-statistic for the first-stage regression of the air quality index and wind velocity is 791.13, 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 0.0031 fatal crashes per day. This effect is statistically significant at the 1% level and represents a 0.84% increase in the mean 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 0.0025 fatal crashes per day. This effect is again significant at the 1% level and represents a 0.69% increase in the mean. The results using 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 0.0009 fatal crashes per day, a 0.25% increase that is statistically significant at the 1% level (Column 3). The results are virtually identical when we include controls (Column 4).

The results for fatalities mirror those for crashes. In the version with controls (Column 2), a one μg/m^3 increase in predicted $PM_{2.5}$ leads to an increase of 0.0026 fatalities per day, a 0.65% increase that is significant at the 5% level. For context, a one standard deviation increase in $PM_{2.5}$ corresponds to a 4.2% increase in motor vehicle fatalities. Using AQI as the measure of pollution yields an increase in fatalities of 0.0008 (Column 4), a 0.19% increase that is statistically significant at the 5% level.

3.3 Robustness Checks

Our results are robust when we switch from Poisson to estimating IV-OLS using a variety of outcome specifications and all are statistically significant, as shown in Table 3. In Column 1 we estimate an Ordinary Least Squares specification with the count of crashes or fatalities as the outcome. Column 2 presents results for a linear probability model where the outcome is whether there were any crashes or fatalities on a given day. In Column 3, we estimate a model using the crash and fatality rate per 100,000 population. Column 4 transforms the outcome variable using the inverse hyperbolic sine. In column 5, the Poisson regression results are unweighted.

We find that a one μg/m^3 increase in predicted $PM_{2.5}$ leads to an increase of 0.0017 crashes and 0.0018 fatalities per day (Column 1). These effects are significant at the 5% level and represent increases of 0.47% and 0.44% relative to the mean. A unit increase in $PM_{2.5}$ also leads to a 0.12 percentage point increase in the probability of any crashes or fatalities, a 0.49% increase that is significant at the 1% level (Column 2). When expressed as a rate per 100,000 people (Column 3) we estimate a 0.84% and 0.75% increase, for each outcome respectively. All estimates for this model are statistically significant at the 1% level. Results are also 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 0.0014 crashes and 0.0015 fatalities (0.39% and 0.38%), which are both significant at the 1% level. The unweighted Poisson regressions yield slightly smaller effect sizes but slightly larger percent effects than the weighted Poisson regressions (Column 5). A unit increase in $PM_{2.5}$ leads to an increase of 0.0011 crashes or fatalities per day. These effects are statistically significant at the 1% level and correspond to a 1.12% and 1.01% increase over the mean.

As a further check that we are observing the true effect of fine particulate matter pollution on crashes as opposed to a spurious correlation, we test for heterogeneous effects by the level of 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.[7] For these regressions, we use actual AQI, as opposed to our predicted AQI instrument, as predicted values of AQI are all 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 state-by-month fixed effects from this estimation because wildfires are concentrated in certain states and months.[8] 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 0.0102 crashes and 0.01 fatalities relative to days where the AQI is 25 or less. These effects are both significant at the 1% and 5% level, respectively. On days when the AQI is between 51 and 100 (moderate air quality), there are 0.0126 additional crashes and 0.0138 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 0.0202 crashes and 0.0180 fatalities. These effects are significant at the 5%

[7]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.

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

level. 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). Appendix Figure A.1 shows plotted coefficients from our fully-specified model with all controls while also including lags of particulate matter concentration 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.

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 attenuated but qualitatively similar. When we instrument for pollution using wind direction and velocity, increases in $PM_{2.5}$ lead to additional car crashes and fatalities.

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 300 times and estimate the model specified in Equation 3 for each random draw for both crashes and fatalities.[9] 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 1 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.[10] 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 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 300 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.[11] In fact, all of the 300 iterations are statistically significant at at least the 10% level. For fatalities, we find that the mean effect size across iterations is 0.00235.[12] These are similarly all statistically significant at the 10% level or more. We conclude from these randomization tests that our result is not due

[9] A total of 600 random matches across both outcome variables.

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

[11] We find a mean z-statistic of 2.89.

[12] We find a mean z-statistic of 2.5.

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 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 0.002 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.[13]

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 4.2% increase in motor vehicle fatalities. Consequently, an across-the-board 1 standard deviation reduction in fine particulate matter pollution would have prevented over 1,500 motor vehicle fatalities in 2019. Using the EPA's value of a statistical life, the pollution abatement efforts required would yield benefits of $11.1 billion per year on the basis of fewer motor vehicle fatalities alone, not even counting reductions in other causes of death. Our results indicate that the negative health and mortality effects of fine particulate matter pollution are more wide-ranging than previously known, making the benefits of reducing air pollution even greater than previously believed.

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

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Tables

Table 1: Summary Statistics

	(1)
PM2.5 Concentration (μ/m^3)	9.7764
	(6.3377)
Air Quality Index	37.6947
	(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

	$PM_{2.5}$	$PM_{2.5}$	AQI	AQI
	(1)	(2)	(3)	(4)
Panel A: Poisson Results				
Crashes	0.0003	0.0001	0.0002**	0.0001
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Mean of Crashes	0.2893	0.2893	0.2893	0.2893
% Effect	0.11	0.03	0.06	0.03
N	1,778,697	1,778,045	1,764,229	1,763,577
Fatalities	0.0004	0.0002	0.0002**	0.0001
	(0.0003)	(0.0002)	(0.0001)	(0.0001)
Mean of Fatalities	0.3104	0.3104	0.3104	0.3104
% Effect	0.14	0.08	0.07	0.05
N	1,778,697	1,778,045	1,764,229	1,763,577
Panel B: Instrumental Variables Results				
Crashes	0.0031***	0.0025***	0.0009***	0.0008***
	(0.0011)	(0.0010)	(0.0003)	(0.0003)
Mean of Crashes	0.3688	0.3688	0.3688	0.3688
% Effect	0.84	0.69	0.25	0.20
N	1,778,697	1,778,045	1,778,697	1,778,045
Fatalities	0.0031**	0.0026**	0.0009**	0.0008**
	(0.0013)	(0.0011)	(0.0004)	(0.0003)
Mean of Fatalities	0.3951	0.3951	0.3951	0.3951
% Effect	0.78	0.65	0.23	0.19
N	1,778,697	1,778,045	1,778,697	1,778,045
County FE	X	X	X	X
State-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		X		X
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 546.15 and the F-statistic for the first-stage regression for predicted AQI is 791.13. 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 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, state-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

	Count (1)	LPM (2)	Rate (3)	IHS (4)	Unweighted (5)
Crashes: $PM_{2.5}$	0.0017^{**}	0.0012^{***}	0.0002^{***}	0.0014^{***}	0.0011^{***}
	(0.0007)	(0.0004)	(0.0000)	(0.0005)	(0.0003)
Mean of Crashes	0.3688	0.2500	0.0227	0.3688	0.0990
% Effect	0.47	0.49	0.84	0.39	1.12
N	1,801,013	1,801,013	1,801,013	1,801,013	1,778,045
Crashes: AQI	0.0005^{**}	0.0004^{***}	0.0001^{***}	0.0004^{***}	0.0003^{***}
	(0.0002)	(0.0001)	(0.0000)	(0.0002)	(0.0001)
Mean of Crashes	0.3688	0.2500	0.0227	0.3688	0.0990
% Effect	0.14	0.15	0.25	0.12	0.33
N	1,801,013	1,801,013	1,801,013	1,801,013	1,778,045
Fatalities: $PM_{2.5}$	0.0018^{**}	0.0012^{***}	0.0002^{***}	0.0015^{***}	0.0011^{***}
	(0.0008)	(0.0004)	(0.0001)	(0.0006)	(0.0003)
Mean of Fatalities	0.3951	0.2500	0.0244	0.3951	0.1067
% Effect	0.44	0.49	0.75	0.38	1.01
N	1,801,013	1,801,013	1,801,013	1,801,013	1,778,045
Fatalities: AQI	0.0005^{**}	0.0004^{***}	0.0001^{***}	0.0004^{***}	0.0003^{***}
	(0.0002)	(0.0001)	(0.0000)	(0.0002)	(0.0001)
Mean of Fatalities	0.3951	0.2500	0.0244	0.3951	0.1067
% Effect	0.13	0.15	0.22	0.11	0.29
N	1,801,013	1,801,013	1,801,013	1,801,013	1,778,045
County FE	X	X	X	X	X
State-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	X	X	X	X	X
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 uses the count of crashes or fatalities as the outcome variable. Column 2 estimates a linear probability model where the outcome is whether any crashes or fatalities occur. Column 3 uses the rate per 100,000 population of crashes or fatalities. Column 4 uses an inverse hyperbolic sine transformation of the outcome variable. Column 5 presents unweighted Poisson regression results. Outcome variables are from the Fatality Analysis Reporting System for 2005-2019 and pollution data are from the Environmental Protection Agency Air Quality Data for 2005-2019. 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, state-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

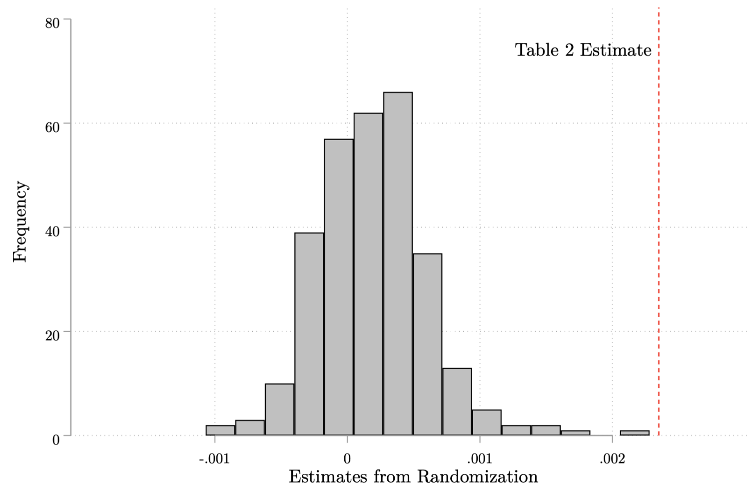
	Crashes (1)	Fatalities (2)
AQI 26-50	0.0102***	0.0100**
	(0.0036)	(0.0043)
AQI 51-100	0.0126***	0.0138***
	(0.0035)	(0.0043)
AQI 101+	0.0202**	0.0180**
	(0.0086)	(0.0088)
Dependent Variable Mean	0.3688	0.3951
N	1,784,293	1,784,293
County FE	X	X
State-by-Month FE		
Month-Year FE	X	X
Day-of-week FE	X	X
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 for 2005-2019 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

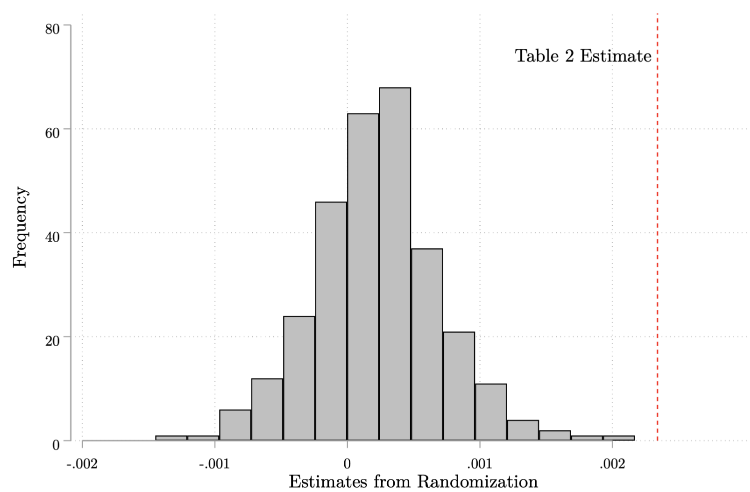
5 Figures

Figure 1: Randomization Tests

Number of Crashes



Number of Fatalities

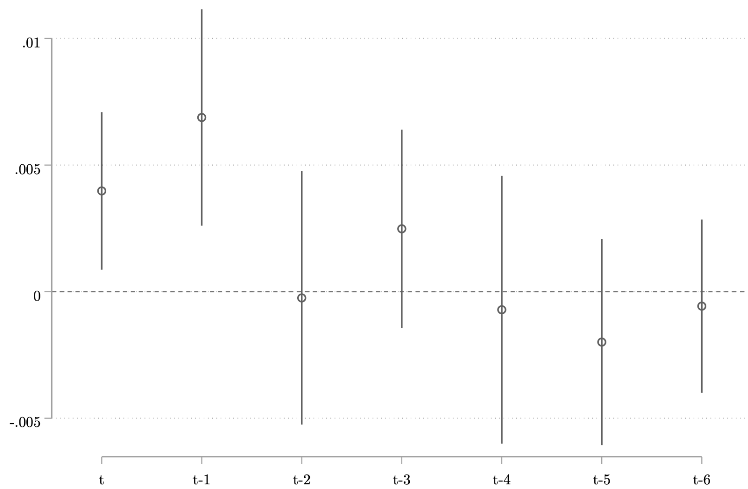


Note: Histogram plots the frequency of estimated coefficients for 300 replications of a randomization exercise in which observations for the dependent variable are randomly matched with particulate matter exposure and controls from another county. The red line plots the estimated coefficient without randomization from the estimation specified in Equation 3 shown in Table 2.

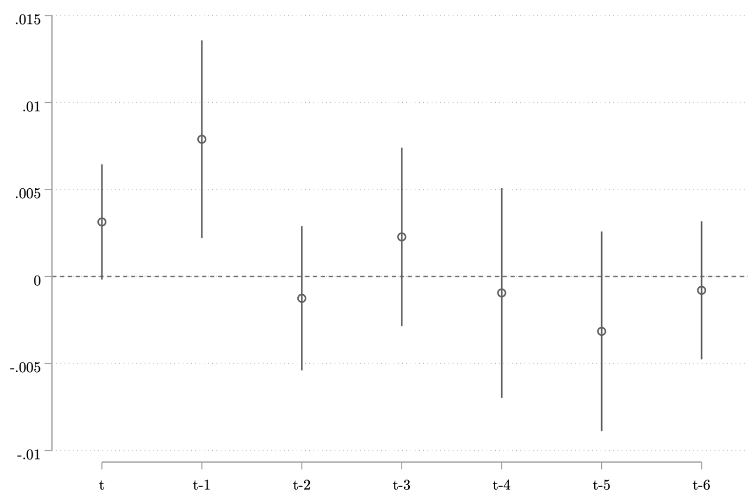
A Appendix Figures and Tables

Figure A.1: Lagged Particulate Matter Exposure

Number of Crashes



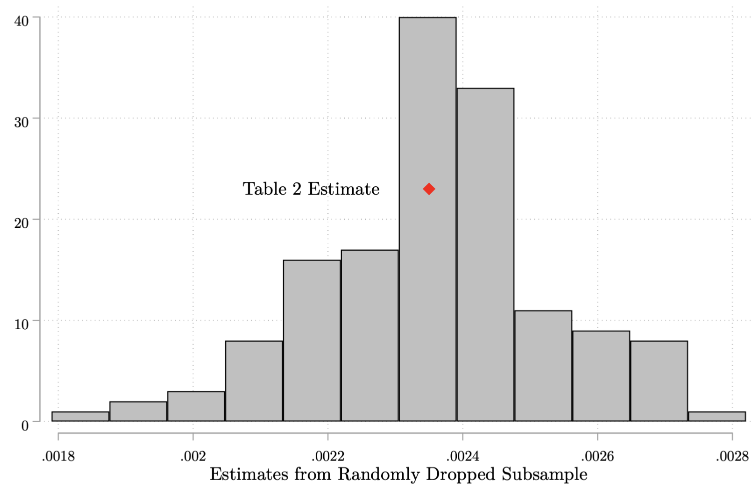
Number of Fatalities



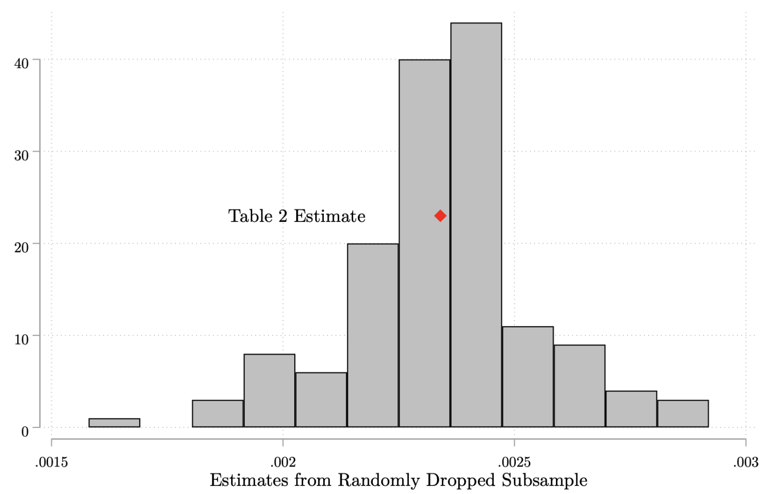
Note: Figure shows plotted coefficients from from the estimation specified in Equation 3 with additional lags of particulate matter exposure included.

Figure A.2: Coefficient Distribution with Randomly Dropped Subsample

Number of Crashes



Number of Fatalities



Note: Figure shows plotted coefficients from 300 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				
Crashes	-0.0001	-0.0003*	0.0000	-0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Mean of Crashes	0.2991	0.2991	0.2991	0.2991
% Effect	-0.03	-0.09	0.01	-0.01
N	2,336,257	2,335,605	2,321,789	2,321,137
Fatalities	-0.0000	-0.0002	0.0001	-0.0000
	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Mean of Fatalities	0.3226	0.3226	0.3226	0.3226
% Effect	-0.00	-0.06	0.02	-0.00
N	2,336,257	2,335,605	2,321,789	2,321,137
Panel B: Instrumental Variables Results				
Crashes	0.0021***	0.0018***	0.0007***	0.0006***
	(0.0007)	(0.0006)	(0.0002)	(0.0002)
Mean of Crashes	0.3870	0.3870	0.3870	0.3870
% Effect	0.56	0.47	0.18	0.15
N	2,336,257	2,335,605	2,336,257	2,335,605
Fatalities	0.0019**	0.0016**	0.0006**	0.0005**
	(0.0009)	(0.0007)	(0.0003)	(0.0002)
Mean of Fatalities	0.4168	0.4168	0.4168	0.4168
% Effect	0.46	0.38	0.15	0.12
N	2,336,257	2,335,605	2,336,257	2,335,605
County FE	X	X	X	X
State-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		X		X
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 200.61 and the F-statistic for the first-stage regression for predicted AQI is 276.79. 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. 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, state-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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.