Does air pollution affect the likelihood of a fatal car crash? Evidence from US

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Abstract

This paper examines the impact of fine particulate matter ($PM_{2.5}$) on fatal car accidents across the United States using instrumental variable (IV) analysis with wind direction as instrument for air pollution. I find that a 1 µg/m^3 increase in $\mathrm{PM}_{2.5}$ levels is associated with a 1.34% increase in daily accidents after accounting for weather conditions and fixed effects. Extending the analysis to hourly data shows that exposure one hour prior to an accident leads to a 1.97% increase in fatal crashes, indicating that short-term pollution impairs cognitive function in real time, increasing accident risks. These findings contribute to the growing body of literature on the behavioral effects of air pollution. The results suggest that the social costs of pollution are underestimated, as its impact extends beyond health outcomes. Policies aimed at reducing air pollution could prevent thousands of fatalities annually and lower healthcare costs.

1 Introduction

Motor vehicle crashes are one of the leading cause of death in the United States. Car accidents are preventable cause of death, and there is a large body of literature examining how various policies affect traffic fatalities. For example, it has been established that policies regarding mandatory seat-belt use (Cohen and Einav (2003)) and drunk driving (Eisenberg (2003)) significantly reduced road fatalities. It is important to note that most literature focuses on policies to which drivers can directly respond and adjust their behavior on the road. Before a policy becomes law, there is a time period during which drivers may prepare to use motor vehicles under a new policy. This paper, however, is a contribution to a limited literature examining drivers' response to exogenous shocks. It is important to know, from policymakers' perspective, if there is a common and unexpected shock that can affect drivers' ability to operate a motor vehicle. This knowledge can be useful for designing effective interventions, such as real-time alerts or temporary restrictions on high-risk driving conditions. Quantifying the risks associated with such shocks allows to conduct a more accurate cost-benefit analysis. Measures like pollution advisories or dynamic speed limits could help mitigate accident risks and save lives, reducing the economic burden of traffic fatalities.

While in Europe the rate of traffic fatalities has been decreasing, in the United States it is on the rise. The European Commission published a report suggesting that during 2019-2022 the motor vehicle fatality rate decreased by 10% in the EU. Simultaneously, according to CDC National Center for Health Statistics, from year 2019 to 2021 there was a 16% increase in motor vehicle fatalities in the United States. Properly understanding what parameters affect the motor vehicle fatality rate can be crucial when designing a policy aimed at reducing it.

In this paper I find that short term exposure to particulate matter leads to a statistically significant increase in road fatalities. These results suggest that the benefits of environmental policy and ameliorating air pollution are underestimated, as improving air quality can result in fewer accidental deaths on the road, which in turn would lead to lower public health expenditures. From a policymaker's perspective, there is a tradeoff between health costs and economic benefits when implementing a tax on air pollution. Understanding the health costs of air pollution is essential for environmental policy proposals. If health costs are not estimated correctly, it will negatively impact the efficiency of environmental policy.

Air pollution is a significant public policy issue with major negative consequences. Multiple studies have shown that exposure to air pollution leads to adverse health outcomes, mainly through respiratory and cardiovascular diseases (Kim, Jahan, and Kabir (2013), Fiordelisi, Piscitelli, Trimarco, Coscioni, Iaccarino, and Sorriento (2017)). Poor air quality imposes a heavy burden on public health expenditures ((Segalowitz (2008)) as chronic diseases and disabilities caused by pollution lead to a large increase in healthcare costs.

Beyond the direct impact on health, air pollution also can also negatively affect economic outcomes. There is a considerable evidence that air pollution has a negative impact on labor productivity (Carson, Koundouri, and Nauges (2011), Rodrigues-Silva, de Paula Santos, Saldiva, Amato-Lourenço, Miraglia et al. (2012), Hanna and Oliva (2015)). Air pollution may affect worker productivity through various channels. The most intuitive way work performance can decline is due to decreased work attendance caused by exposure to poor air quality. Another, less obvious channel through which air pollution can decrease productivity, is a decline in cognitive functioning due to being exposed to air pollutants. This can lead to increase in operation business costs. Overall, the negative effects of air pollution on the cognitive system are well-studied (Hausman, Ostro, and Wise (1984)).

Given that exposure to air pollution has been shown to impair cognitive functioning, it is reasonable to expect a negative impact on tasks requiring focus and quick decision-making, such as driving. Driving a motor vehicle demands sustained attention and quick reflexes, all of which may deteriorate under the influence of pollutants like particulate matter ($PM_{2.5}$). If air pollution negatively impacts these cognitive actions, drivers are more prone to errors and delayed reactions on the road, which could lead to an increase in traffic accidents. It is plausible that higher levels of air pollution would correlate with a rise in car fatalities as drivers are cognitively impaired.

Studies have also linked air pollution to impaired real-time decision-making, showing increased errors among highly skilled professionals (Archsmith, Heyes, and Saberian (2018)). While these errors often occur in relatively low-risk settings, driving involves rapid, high-stakes decisions where even small mistakes can lead to fatal accidents. This makes the decline in cognitive function caused by pollution exposure particularly dangerous on the road. Research on the effects of air pollution on mortality has predominantly focused on internal causes of death and hospitalizations (Deryugina, Heutel, Miller, Molitor, and Reif (2019)). However, the consequences of air pollution extend beyond these severe health outcomes, posing immediate risks to public safety.

In this paper I estimate the magnitude of short-run effect of exposure to $PM_{2.5}$

on fatal car accidents in the United States. Using air quality data from the Environmental Protection Agency (EPA) and traffic fatality data from the Fatality Analysis Reporting System (FARS), I aggregate pollution and accident data to the county-day level over the period from 1999 to 2013. The main concern when estimating the causal impact of air pollution on traffic fatalities is that exposure to air pollution is not randomly assigned, which can lead to biased estimates. To address this, I use an instrumental variable (IV) approach, exploiting daily variations in wind direction as an exogenous source of variation in pollution levels. After accounting for weather conditions and fixed effects, I assert changes in a county's wind direction only affect fatal car crashes through the impact on air pollution, and that wind direction satisfies the exclusion restriction as an instrument. By using variation in wind pattern, I isolate the effects of air pollution on traffic mortality rate. A key benefit of the instrumental variable methodology is that it eliminates the need to isolate the source of pollution. This is particularly important in the context of air quality studies, where multiple emission sources—such as industrial facilities, vehicle traffic, and natural events like wildfires—can simultaneously contribute to pollution levels. By using exogenous variation, such as changes in wind direction, the IV approach allows me to isolate the impact of pollution on traffic accidents, without needing to take the source of pollution into account.

My main air pollutant of interest is $PM_{2.5}$. Particulate matter (PM) consists of tiny solid and liquid particles suspended in the air, and it is regulated by the EPA. Fine particles under 2.5 micrometers in diameter, including combustion particles, metals, and organic compounds, are called $PM_{2.5}$. Not only do these smaller particles enter the lungs but they also reach the bloodstream.

Natural sources of $PM_{2.5}$ include volcanic eruptions and wildfires, while anthropogenic sources come from fossil fuel combustion in power plants, industries, and vehicles. $PM_{2.5}$ can remain airborne for extended periods and travel long distances and penetrate buildings unless the buildings are equipped with air filtering system. Long-term exposure to $PM_{2.5}$ is associated with premature death, particularly in individuals with chronic heart or lung diseases, as well as impaired lung development in children.

I find that a one microgram per cubic meter (μg/m$^{\mathbf{3}}$) increase in $PM_{2.5}$ levels leads to a 0.0009 increase in daily fatalities per county. This finding suggests that a one (μg/m$^{\mathbf{3}}$ increase in $PM_{2.5}$ corresponds to approximately a 1.34 percent increase in fatal car accidents, or roughly 550 additional deaths annually across the United States. Using the value of a statistical life (VSL) which is commonly used by policymakers to quantify the economic value of reducing mortality risks, this translates to $4.06 billion. These results hold after controlling for temporal variation in atmospheric conditions such as wind speed, temperature, and precipitation, as well as geographic fixed effects to account for seasonal and regional variations in both air quality and traffic patterns. This paper provides more rationale for adopting stricter air quality standards and pollution reduction policies, since true costs of pollution might be underestimated.

In addition to the daily analysis, I extend the study to examine how immediate exposure to pollution affects road safety using hourly data from 2010 to 2013. The hourly results reveal that a 1 µg/m$^{\mathbf{3}}$ increase in $\mathrm{PM}_{2.5}$ levels leads to a 1.97% increase in fatal car crashes. These findings highlight the cognitive effects of pollution on drivers' decision-making and reaction times. Including day-of-week fixed effects in the hourly analysis is important as it allows me to capture weekday and weekend driving patterns that influence accident likelihood. This more granular approach demonstrates how pollution's impact on real-time driving safety is not uniform throughout the day but fluctuates with variations in traffic intensity and driving behavior.

The relationship between the daily and hourly results reveals how pollution affects drivers over different time frames. While the daily analysis suggests that pollution exposure throughout the day increases accident risks, the hourly analysis indicates that short-term exposure, specifically in the hour leading up to an accident, has a slightly larger impact. . Together, the daily and hourly findings suggest that both accumulated and immediate exposure to pollution matter, but immediate exposure may be especially detrimental in high-risk situations, such as those requiring quick reflexes and real-time decision-making.

This paper builds on the methodology from Deryugina et al. (2019), using their instrumental variable (IV) strategy to establish causality between air pollution and adverse health or safety outcomes. The validity of an IV approach holds as daily variations in wind direction are strongly correlated with the endogenous variable, in this case, $PM_{2.5}$ levels. Deryugina et al. have established that changes in wind direction are a good predictor of local pollution concentrations. The exclusion restriction, which assumes that wind direction impacts car accidents only through its effect on pollution, not through other channels, holds. I am able to isolate the short-term effects of particulate matter on traffic safety, reducing potential bias in my estimates that might arise from confounding factors like driving patterns or regional economic conditions.

This paper contributes to growing literature on negative effects of air pollution on cognitive functioning. Previous studies have documented the impact of air pollution on labor productivity (He, Liu, and Salvo (2019)) and crime rates (Herrnstadt, Heyes, Muehlegger, and Saberian (2021)) through a decline in cognitive function. The role of air quality in traffic safety has been less explored. By estimating the extent to which short-term exposure to $PM_{2.5}$ can increase fatal car crashes, my findings highlight the broader societal costs of pollution and its influence on cognitive function in high-stakes, real-time decision-making scenarios. The paper closest to mine is Sager (2019). It examines the impact of air pollution on road safety in the United Kingdom between 2009 and 2014. Using temperature inversions as a source of exogenous variation, they find that a $1\mu g/m$ increase in $PM_{2.5}$ levels leads to a 0.3–0.6% increase in the number of vehicles involved in road accidents per day. My results are consistent with those findings. It is interesting to consider this question in the context of the United States because people in the United States rely on cars way more than in the United Kingdom and in general the attitude to driving is different culturally. The closest paper to mine is Burton and Roach (2023), which examines how exposure to particulate matter pollution impairs cognition and increases fatal car crashes. My paper extends this analysis by taking into account hourly observations. This more granular approach illustrates how fluctuations in pollution within a single day influence driving safety.

The remainder of this paper is organized as follows. Section 2 provides background information on particulate matter (PM), describing the different types of PM and their sources, as well as the health risks associated with exposure. Section 3 outlines the data sources used in this paper. In Section 4, I present the identification strategy and empirical methodology. Section 5 discusses the results. In Section 6 I present my results for hourly level analysis. Finally, Section 7 concludes the paper by summarizing the findings and their implications for public policy.

2 Background on PM (particulate matter)

Particulate matter is a term used to describe microscopic particles of solid and liquid matter suspended in the air. There are two types of particles that are regulated by the Environmental Protection Agency (EPA) in the US. Particulate matter with diameter of between 2.5 and 10 micrometers are called "coarse particulates," while PM less than 2.5 in diameter are called "fine particulates."

PM_{10} particles are inhalable particles less than 10 micrometers in diameter. For example, dust, pollen, and mold are PM10 particles. These particles are small enough to get into the lungs. Exposures to PM10 have been linked to the worsening of respiratory diseases, such as asthma, leading to hospitalization and emergency department visits.

$PM_{2.5}$ particles are inhalable particles less than 2.5 micrometers in diameter. For example, combustion particles, metal, and organic compounds can be $PM_{2.5}$ particles. These particles are small enough to get into the lungs and enter the bloodstream. The main natural sources of $PM_{2.5}$ are volcanic eruptions and wildfires. As for anthropogenic sources, they include fossil fuel combustion from power plants, industries, and automobiles. They can stay in the air for a long time and travel for hundreds of miles. They can enter buildings: hence, many people are easily exposed to it. Long-term exposure to $PM_{2.5}$ has been associated with premature death, particularly in people who have chronic heart or lung diseases, and reduced lung function growth in children.

$PM_{2.5}$ is considered to be the most dangerous form of air pollution from a public health perspective. Once $PM_{2.5}$ enters the lungs and bloodstream, it has been linked to a range of cardiovascular and respiratory diseases, including heart attacks, strokes, chronic obstructive pulmonary disease (COPD), and lung cancer (Pope, Burnett, Thun, Calle, Krewski, Ito, and Thurston (2002); Brook, Rajagopalan, Pope III, Brook, Bhatnagar, Diez-Roux, Holguin, Hong, Luepker, Mittleman et al. (2010); Dockery, Pope, Xu, Spengler, Ware, Fay, Ferris, and Speizer (1993)). Long-term exposure to high levels of $PM_{2.5}$ is also associated with premature death, particularly in vulnerable populations, such as those with existing heart or lung conditions Hoek, Krishnan, Beelen, Peters, Ostro, Brunekreef, and Kaufman (2013); Pope and Dockery (2006). $PM_{2.5}$ can remain suspended in the air for a long time and travel significant distances - even thousands of miles - from the source. If pollution originates in industrial regions, it can still affect rural areas or areas much further away from it. Additionally, $PM_{2.5}$ particles can penetrate indoor environments, making it difficult to avoid exposure, even when indoors. The negative effects of being exposed to $PM_{2.5}$ go beyond cardiovascular issues. Recent studies show that $PM_{2.5}$ can also affect the cognitive functioning of the human brain (Weuve, Puett, Schwartz, Yanosky, Laden, and Grodstein (2012)) . Particulate matter can cross the blood-brain barrier, which can cause inflammation in the brain, leading to problems with memory, decision-making and ability to concentrate (Calderon-Garciduenas, Franco-Lira, Torres-Jardon, Henriquez-Roldan, Barragan-Mejia, Valencia-Salazar, Gonzales-Maciel, Reynoso-Robles, Villarreal-Calderon, and Reed (2008)). This is especially concerning for activities like driving, where full attention and quick thinking are crucial.

One of the main reasons $PM_{2.5}$ is used as my pollution marker is that it is the most consistently monitored pollutant. The EPA has provided comprehensive data on $PM_{2.5}$ since 1999. Data for other pollutants monitored by EPA, such as nitrogen dioxide (NO_2), sulfur dioxide (SO2), ozone (O3), carbon monoxide (CO), lead and larger particulate matter ($PM10$), are much less consistently available over time and across places.

3 Data

3.1 Data on air pollution

Air pollution data for pollutants regulated by the Clean Air Act ($PM_{2.5}$, ozone, carbon monoxide, sulfur dioxide, nitrogen dioxide) and PM_{10} are taken from the Environmental Protection Agency (EPA) Air Quality database. I am using dataset from Deryugina et al. (2019) that contains information on all pollutants at the monitor level. The data are provided at pollution-monitor level. All available monitor readings within counties are averaged to obtain county-level measures. My pollutant of interest is $PM_{2.5}$ and I use data at the daily level. For the daily analysis, I analyze interval from 1999 to 2013, as the comprehensive data for $PM_{2.5}$ is available from 1999. Figures 1 and 5 show the change of fine particulate matter levels over time in the United States over the 1999-2013 time period is presented. The average $PM_{2.5}$ levels steadily decline over time, from 13.6 $\mu g/m^3$ (micro-grams per cubic meter) in year 1999 to 8.1 $\mu g/m^3$ in year 2013. Number of pollution monitors remained approximately the same since year 2001. It is important to note that according to Sullivan, Krupnick et al. (2018), counties can strategically place pollution monitors in cleaner areas, which can potentially bias the results. Instrumental variable specification helps eliminate this source of bias, so changes in monitored counties should not affect this analysis.

Although only about a third of U.S. counties are covered by pollution monitors, this is not a significant limitation for my analysis. The monitors are primarily located in more populated and urban areas, where both traffic and pollution levels are higher. Since these areas represent a substantial share of economic activity and human exposure, the available data are representative. With this coverage, I am able to capture 64% of all car accidents during the study period. While rural areas may have less monitoring, these regions also tend to experience fewer accidents.

On average, $PM_{2.5}$ levels start relatively high in January, with concentrations around 11 μ g/m$^{\mathbf{3}}$, then steadily decline to a low of approximately 8 μg/m$^{\mathbf{3}}$ by April. However, concentrations rise sharply through the spring, reaching a peak of nearly 12 μg/m$^{\mathbf{3}}$ in July. After this summer high, the concentration drops again, hitting its lowest point of the year—just over 9 μg/m$^{\mathbf{3}}$.

This pattern can be explained by a combination of seasonal factors. The mid-year rise in $PM_{2.5}$ concentrations, especially in June and July, likely corresponds to higher traffic due to summer travel, and possibly wildfires in certain regions. These months tend to see more outdoor activities, which often contribute to higher pollution levels. On the other hand, the elevated $PM_{2.5}$ levels in January and December could be driven by increased heating during the colder months, with more homes and businesses burning fuel for warmth, leading to higher emissions. The sharp decline in spring and late fall reflects a period of reduced heating and potentially less travel or industrial activity, helping to lower pollution levels during those months.

3.2 Data on car accidents

Data on fatal car accidents level is obtained from the Fatality Analysis Reporting System (FARS). It records every fatal car accident on public roads in the United States. I aggregate FARS data to represent county-daily measure. On average there is one fatal car accident in a county in a day. Figure 2 represents the raw trend in car accidents over my time period of interest. On average there is from 19000 to 24000 fatal car accidents in a year in the United States in the areas where air pollution is monitored.

The trend in accidents shows a steady rise from January, starting at around 2,000 accidents, and peaking in July with approximately 3,000 accidents. After July, the total number of accidents gradually declines, with the year ending in December at just over 2,500 accidents. The increase in accidents from winter to mid-summer likely reflects several external factors. For example, summer months see a surge in travel, with more people on the road for vacations, contributing to the rise in accidents from about 2,000 in January to 3,000 in July. Additionally, summer hazards like heavy rains or extreme heat in certain regions may also elevate the risk of accidents. The decline after July could be attributed to a reduction in travel as the vacation season ends, causing the number of accidents to drop from 3,000 in July to around 2,500 by December. This decrease may also reflect improved weather conditions in some regions as summer storms subside. Furthermore, as people return to their regular routines and school begins, there may be more incentives to be cautious while driving, contributing to the decline.

3.3 Data on atmospheric conditions

Data on wind direction and wind speed for year 1999-2013 is available from the North American Regional Reanalysis (NARR) daily reanalysis data. Wind direction is defined as the direction the wind is blowing from, for example, if wind direction is SW, it means the wind is blowing from the South-West. Clean data on wind direction is obtained from Deryugina et al. (2019). Wind direction and wind speed is reported for 32 by 32 kilometer grid and averaged at county-daily level.

Other control variables such as maximum and minimal temperatures and precipitation rates are obtained from Schlenker and Roberts (2009) who provide methodology to produce 2.5 by 2.5 mile grid using data from PRISM and weather stations. Once again, county-daily measures are used in this paper.

4 Identification and Empirical strategy

I am estimating short run effect of exposure to fine particulate matter on the likelihood of getting in a fatal car crash. The relationship can be described by the following equation

$$Y_{dmyc} = \beta PM2.5_{dmyc} + \theta X'_{dmyc} + \sigma_c + \sigma_d + \sigma_{my} + \sigma_{sm} + \epsilon_{dmyc} \tag{1}$$

where the dependent variable (Y_{cdmy}) is the number of fatal car accident in county c, on day d, in month m in year y. β, the main coefficient of interest is on the daily level of fine particulate matter $PM_{2.5}$. A vector of time-varying control variables is represented by X_{dmyc}. In this model, I also control for extremely high temperature levels (above $85°F$) and extremely low temperatures (below freezing), indicators for precipitation rates in deciles and wind speed in miles per hour. To account for geographic differences in car traffic and air pollution, I include county (σ_c) fixed effects. State-by-month fixed effects ((σ_{sm}) control for any seasonal correlation between car accidents, wind direction and air pollution, as well as allowing for this correlation to vary by state. Month-by-year fixed effects (σ_{my}) account for common time-varying shocks, such as those induced by any environmental or car-related policy changes during the period of this study. Standard errors are clustered at the county level. The interval I am considering for my analysis at daily level spans 1999 to 2013. My methodology is based on Deryugina et al. (2019).

OLS estimates are very likely to be biased for various reasons. First of all, exposure to fine particulate matter is not randomly assigned. Pollution monitors' locations are not random, with higher monitor counts typically showing up in areas with higher population density. This non-random placement implies that monitor readings might not fully record actual exposure faced by all individuals in a county, leading to underestimated or overestimated levels of pollution exposure, depending on the local geography. Furthermore, people can drive through areas with different levels of pollution than where they live or are typically exposed. This creates a potential discrepancy between the monitor readings and the actual exposure of drivers, introducing measurement error and potentially leading to downwards bias in OLS estimates since measurement error is misrepresenting the actual exposure to pollution. Overall, the presence of measurement error and omitted variable bias is very likely. I exploit variation in air pollution due to changes in daily wind direction in order to estimate the causal effect of exposure to fine particulate matter on getting into a car accident. The key identifying assumption of my instrumental variables (IV) model is the exclusion restriction that states that controlling for weather variables and fixed effects, changes in the county's daily wind direction only affect accidents through air pollution. Using exogenous variation in wind direction will help isolate exposure to air pollution. The instrumental variable methodology eliminates some of the biases present in OLS by isolating pollution exposure from its source, focusing on variation in air pollution caused by wind rather than relying on the non-randomly placed monitors. This method addresses the concern that pollution exposure is correlated with other unobserved factors, such as local driving behaviors or economic activity, that could also influence motor vehical fatalities.

My first stage equation is defined the following way

$$PM2.5_{cdmy} = \sum_{g \in G} \sum_{b=0}^{2} \beta_b^g 1[G_c = g] * WINDDIR_{cdmy}^{90b} + X'_{cdmy} + \gamma_c + \gamma_{ms} + \gamma_{my} + \epsilon_{cdmy} \tag{2}$$

where $PM2.5_{cdmy}$ represents the fine particulate matter levels in county c, on day d, in month m in year y. Variables $1[G_c = g] * WINDDIR_{cdmy}^{90b}$ are the excluded instruments. Wind directions are split into four 90-degree bins $[90b, 90b + 90]$ such that $b \in \{0, 2\}$. Excluded reference bin is $[270, 360]$, which represents the West-Northwest wind direction. Results are robust to increasing the number of bins and coefficients are very similar if i change the range of b to $b \in \{0, 7\}$ splitting wind direction into 8 bins. For the purpose of reducing the computational burden of this model I am sticking to $b \in \{0, 2\}$. Vector of controls X'_{dmyc} and fixed effects are defined in equation (1).

Monitor locations within counties are quite widespread, as a result, pollution-monitor readings in a county might misrepresent the actual average fine particulate matter exposure for county residents. In Deryugina et al. (2019), k-means cluster algorithm is used to classify all the pollution monitors in the United States into a hundred spatial groups based on their location. Grouping counties into spatial clusters based on proximity to monitors can help avoid the issue of sparse monitoring. Neighboring monitors are more likely to be assigned to the same group than the monitors far away from each other. On average each geographic group contains 21 monitors and 9 counties. Indicator for a county c being assigned to a group g from the set of monitor groups $\mathbf{G}$ is represented by the variable $1[G_c = g]$. This group division eliminates the issue of sparse monitor locations and limits the effect of wind direction in a county on its air pollution level to be the same within all counties assigned to a specific geographic area. Potential measurement error is also addressed through this approach. It is expected that the impact of the local sources of pollution emission will differ within a monitor group, based on the relative location of pollution monitor and pollution source. By splitting counties into different groups geographically, the impact of variation due to locally produced pollution is reduced. The most relevant example of locally produced pollution in this context is the pipe emissions from cars that can contain fine particulate matter. It is important to note here that another thing generating measurement error is that locally produced pollution is unlikely to reach all the people within the monitor group. However, the non-local pollution sources located on either side of the whole monitor group are expected to have the same effect on all monitors within the group which makes non-local pollution emission likely to determine the variation in air pollution levels analyzed in equation (2), which is also helpful to reduce measurement error.

Coefficient of interest is β_b^g which represents the interaction between fine particulate matter and wind direction. It varies geographically between 100 assigned groups and between 4 different wind direction bins.

Wind direction as an instrument for air pollution is a commonly used instrument, and since it is a strong predictor of pollution levels, weak instrument is not a concern within this setting. My final specification has **N=3x100=300** instruments and my first stage F-statistics is sufficiently large and is equal to 370.5.

5 Results for daily analysis

I start with the potentially biased ordinary least squares regression results with and without controls are presented in Table 2. Results of the instrumental variable specification with and without controls are presented in Table 5. The OLS estimates of effect of air pollution are statistically significant and show that a one $\mu g/m^3$ increase in the levels of fine particulate matter leads to an increase of 0.0002 in fatalities per capita. This effect is very small and represents a 0.02% increase. It becomes even smaller after controlling for atmospheric variables, signifying only a 0.001 increase in fatalities. Pollution exposure is often measured with error, as monitors may not capture the true exposure experienced by all drivers across a county. This measurement error biases the OLS coefficient toward zero.

To alleviate potential downwards bias from measurement error and omitted variables, I am using IV specification. The IV results are statistically significant at a 1% level and suggest that a one $\mu g/m^3$ increase in the levels of fine particulate matter lead to increase of 0.0036 fatalities in a county per day. The results are summarized in Table 4, with three models: (1) no controls or fixed effects,

(2) with weather controls and county, month-year and state-month fixed effects, and (3) adding day-of-week fixed effects. The percentage change indicates that in the baseline model (column 1), a 1 µg/m^{3} increase in $PM_{2.5}$ corresponds to a 5.43% increase in daily crashes. Adding controls for extremely high and low temperatures, wind speed and precipitation rate, as well as fixed effects (column 2) reduces the effect to 1.34%. Including Day-of-Week fixed effects (column 3) only slightly alters the effect to 1.35%. This suggests that controlling for driving behavior throughout the week does not substantially affect the relationship between air pollution and crashes. The addition of weather controls, such as precipitation and temperature, significantly reduces the estimated effect. This suggests that part of the observed relationship in the baseline model could be attributed to weather factors. Fixed effects for counties, state-month, and month-year also improve model precision, reflected by the increase in the F-statistic from 370.5 to over 3,000 across the models. The stability of the $PM_{2.5}$ coefficient with and without the Day-of-Week fixed effects indicates that pollution's impact on crashes is not driven by differences in weekday traffic patterns at the daily scale. Negative sign of coefficients for wind speed and precipitation rate is consistent with the literature. Higher wind speeds and precipitation may reduce crash frequency as drivers become more cautious, reduce speed, or avoid travel altogether during poor weather conditions. (Knapp, Kroeger, Giese et al. (2000)).

My final specification has **N=3x100=300** instruments and my first stage F-statistic is sufficiently large and is equal to 370.5, which is above the threshold to ensure no weak instrument bias. In other words, a one standard deviation increase in the levels of fine particulate matter leads to a 9% increase in daily fatal car crashes, which translates to approximately 2700 fatal crashes a year.

Fatal car crashes impose a substantial economic burden through medical costs. Reducing levels of $PM_{2.5}$ by one standard deviation could lead to a decrease in fatal car crash level by 2700 accidents a year on average. Using the value of a statistical life (VSL)—which is currently estimated at \$7.4 million by the U.S. Environmental Protection Agency (EPA (2006))—the potential economic cost of these additional 2700 fatalities amounts to \$19 billion per year. This number represents the economic value of the lives lost due to traffic accidents driven by higher pollution levels and does not account for the further costs associated with non-fatal injuries, disabilities, or the long-term impacts on healthcare systems. The indirect effects, such as the strain on emergency response services, long-term healthcare costs, and psychological effects on victims' families, would add to the overall societal costs. These results highlight the benefits of environmental policy, not only through addressing health concerns but also through reducing motor vehicle fatalities. A well-designed policy could significantly improve both public health and road safety. Lowering $PM_{2.5}$ levels has the potential to save thousands of lives annually and avoid billions in economic costs.

Between 1999 and 2013, average concentrations of $\mathrm{PM}_{2.5}$ fell by approximately 40%, from around 13.6 $\mu g/m^3$ to 8.1 $\mu g/m^3$ (Figure 5). This decline could translate to significant reductions in fatal car accidents. With my findings showing that a 1 $\mu g/m^3$ increase in $\mathrm{PM}_{2.5}$ leads to a 1.34% increase in daily accidents, a 5.5 $\mu g/m^3$ reduction (approximately 40%) would correspond to a 7.4% decrease in fatal crashes.

Fatal accidents and $PM_{2.5}$ concentrations on average both peak in July. The rise in summer travelling could partially explain why we see more accidents and higher air pollution, as more vehicles on the road naturally lead to more emissions and a higher likelihood of traffic incidents. I argue that the cognitive effects of air pollution could also explain variation in fatal car accidents rate. When $PM_{2.5}$ concentrations are high—especially in busy, densely populated areas—it could impair drivers' attention, slow their reaction times, and impact decision-making. To ensure that I am not simply capturing the effect of summer's high temperatures, I control for extreme heat (above 85°F), which could affect both pollution and accidents. Additionally, the use of month-by-year and state-by-month fixed effects accounts for broader seasonal patterns and region-specific differences to help isolate the effect.

6 Hourly estimates

This paper estimates the short-term effect of exposure to fine particulate matter (PM2.5) on fatal car crashes in the United States, using hourly data from 2010 to 2013. To address potential endogeneity and measurement error, I employ an instrumental variable (IV) approach, where hourly variations in wind direction serve as an exogenous instrument for PM2.5.

The equation I am estimating can be described as follows:

$$Y_{hmyc} = \beta\,\mathrm{PM}_{hdmyc} + \theta X'_{hdmyc} + \sigma_c + \sigma_{sm} + \sigma_{my} + \sigma_d + \epsilon_{hdmyc}$$

The results of the IV regressions using hourly data are summarized in Table 5. Column (1) presents the baseline IV regression without any controls or fixed effects. The coefficient on $\mathrm{PM}_{2.5}$ is positive and statistically significant, indicating that an increase in air pollution correlates with more fatal car crashes. In Column (2), I add weather-related controls (precipitation, wind speed, extreme temperature) along with County, State-Month, and Month-Year fixed effects. This specification ensures that the results are not confounded by seasonal patterns, regional driving behaviors, or temperature extremes. The coefficient on $PM_{2.5}$ decreases slightly but remains statistically significant, suggesting an effect of air pollution on road safety after accounting for weather. Column (3) further adds Day-of-Week fixed effects to account for behavioral differences in driving patterns across weekdays and weekends. With these additional fixed effects, the $PM_{2.5}$ coefficient remains significant.

The coefficient on $PM_{2.5}$ in Column (3) suggests that a 1 $\mu g/m^3$ increase in hourly PM2.5 concentration leads to an increase of 0.000071 fatal crashes per hour. Given the average number of fatal crashes per hour is 0.0036, this effect translates into a 1.97% increase in fatal crashes. Similarly, in the baseline model (Column 1), the PM2.5 coefficient implies a 7.36% increase in fatal crashes per hour. This decrease in the estimated percentage effect across models suggests that some of the variation initially attributed to $PM_{2.5}$ may be explained by weather conditions or driving patterns across different days of the week. The change in percentage effect from 0.44% to 1.97% reflects how hourly data captures patterns that can't be seen in daily data. Driving habits change throughout the day, for example, rush hours, late nights, and weekends all have distinct traffic patterns that influence accident risks. Including day-of-week fixed effects with hourly data can help to account for these fluctuations.

The negative coefficients on precipitation and wind speed align with previous findings in the literature. Higher wind speeds and precipitation may reduce crash frequency as drivers become more cautious, reduce speed, or avoid travel altogether during poor weather conditions. (Knapp et al. (2000)).

7 Discussion

In this paper, I look at how exposure to fine particulate matter $PM_{2.5}$ affects fatal car crashes in the United States. I estimate the effects of air pollution on traffic safety using hourly and daily data through an instrumental variable (IV) approach. Across six different model specifications, the findings show how pollution impacts accident risk in both the short and slightly longer term.

My main result is that a 1 µg/m^3 increase in $PM_{2.5}$ leads to a 1.34% increase in daily accidents after accounting for weather conditions and fixed effects, down from an initial 5.43% with no controls. This decrease suggests that factors like temperature, precipitation, and wind speed influence traffic safety independently of pollution.

I also find that being exposed to air pollution one hour prior to the accident increases the chances of getting into one. More specifically, a 1 µg/m^3 increase in particulate matter levels results in a 1.97% increase in fatal accidents when controlling for day-of-week fixed effects. It is important to note that not taking into account day-of-week fixed effects reduces the estimate significantly, and the estimated effect is just 0.44%. It suggests that traffic patterns on weekdays and weekends mask some of the underlying impact of pollution that can't be captured when data are aggregated at daily level.

While accumulated exposure to poor air quality matters, the hourly analysis suggests that immediate exposure to pollution—like breathing in dirty air just before getting on the road—can impair drivers in real-time, reducing their ability to make quick decisions. This explains why the effect of pollution on accidents becomes more pronounced when using granular data, especially with day-of-week fixed effects to capture behavioral differences. Overall, these findings suggest that reducing pollution could save lives through this channel.

This paper highlights the value of environmental policies aimed at reducing pollution. Reducing $PM_{2.5}$ concentrations by even a small amount could lead to fewer accidents, less strain on emergency services, and lower public health costs.

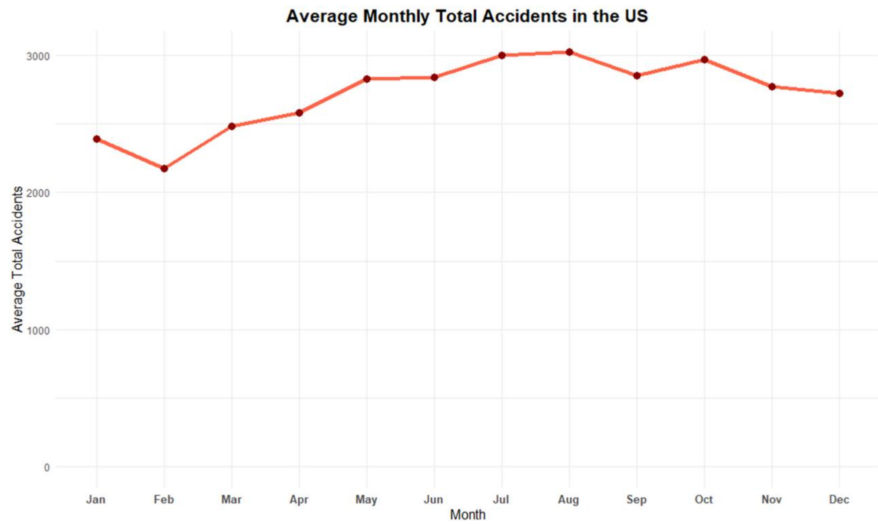


Figure 1: Average Monthly Total Accidents in the US

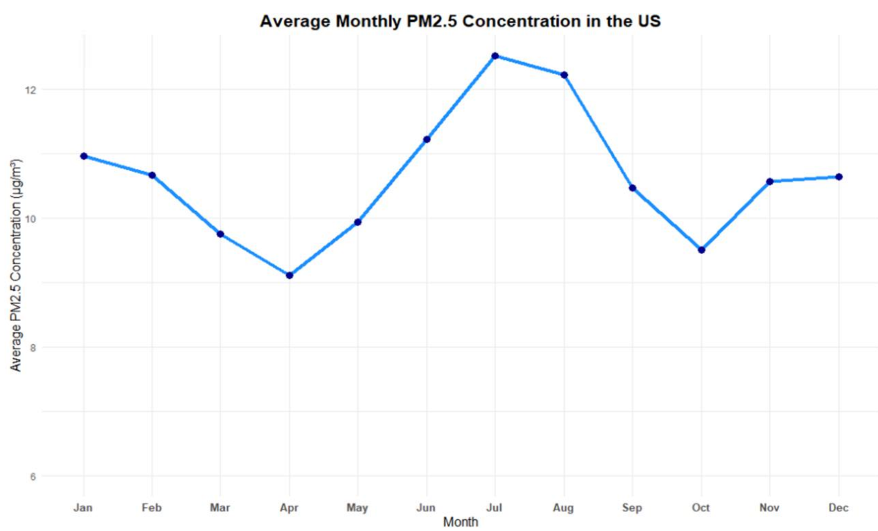


Figure 2: Average Monthly $PM_{2.5}$ Concentration in the US

Figure 3: These graphs show the monthly averages of total accidents and$PM_{2.5}$ concentrations across the United States for the years 1999-2013. The first graph illustrates the average total number of accidents per month, while the second graph shows the average concentration of $PM_{2.5}$ (fine particulate matter). The seasonal patterns in both graphs indicate potential correlations, particularly in the summer months, where higher pollution levels and increased accident rates coincide.

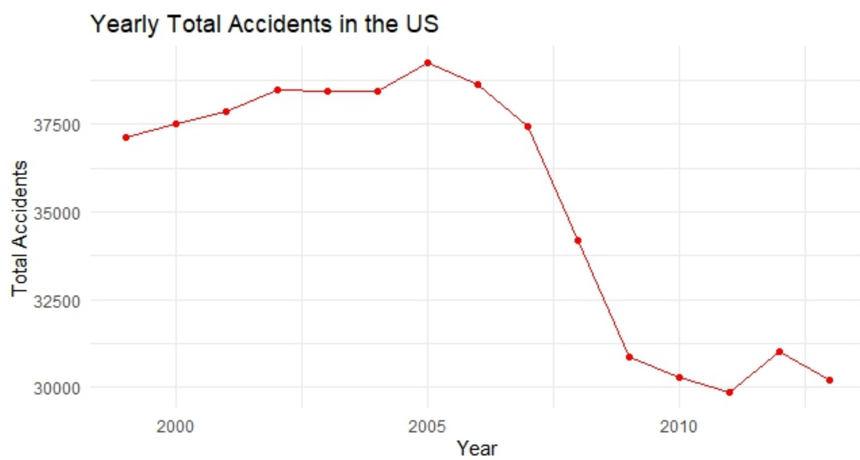


Figure 4: Average Yearly Total Accidents in the US

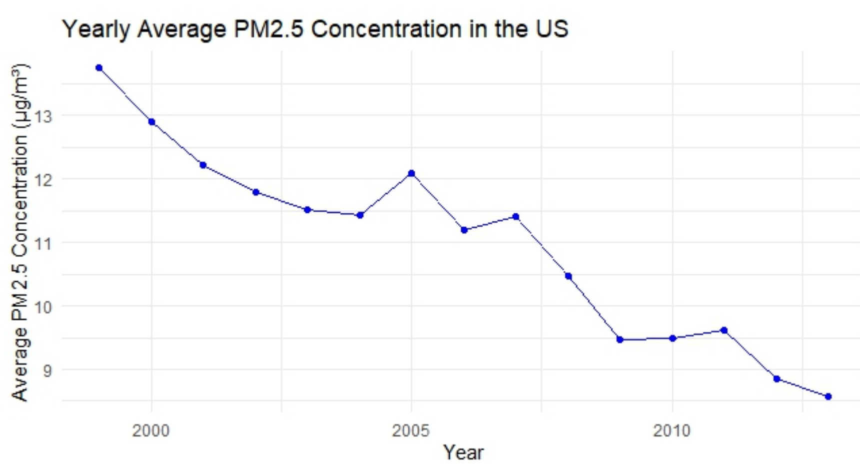


Figure 5: Average Yearly $PM_{2.5}$ Concentration in the US

Figure 6: These graphs display the yearly variations of total accidents and $PM_{2.5}$ concentrations across the United States. The first graph illustrates the total number of accidents per year, while the second graph shows the average concentration of $PM_{2.5}$.

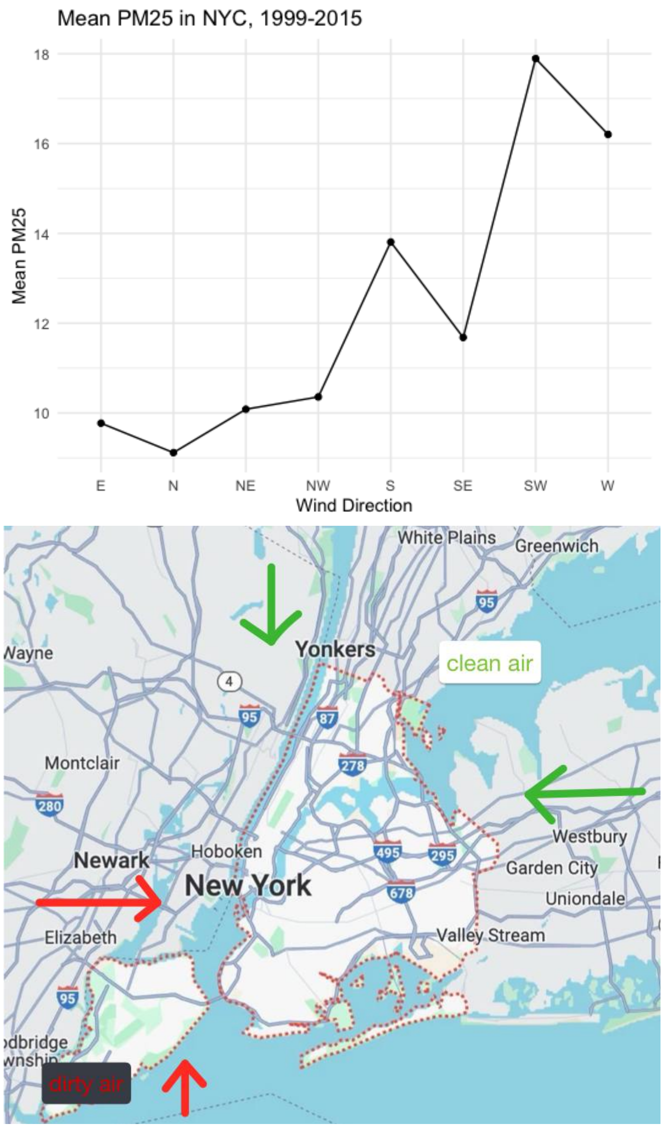


Figure 7: **New York City: daily $PM_{2.5}$ concentrations and wind direction.** This figure shows first stage results for New York City area, with dependent variable being $PM_{2.5}$ levels, and independent variable being wind direction. Control variables and fixed effects are accounted for. Results are consistent with what is expected - if the wind blows from South-West (New Jersey), recorded air quality is low, and if the wind blows from the East (the ocean), recorded air quality is high.

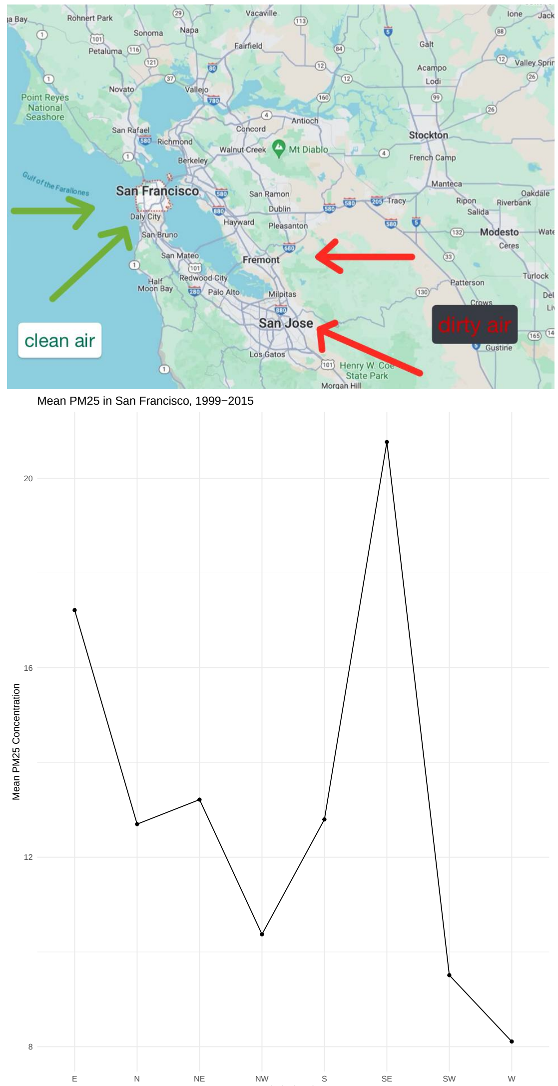
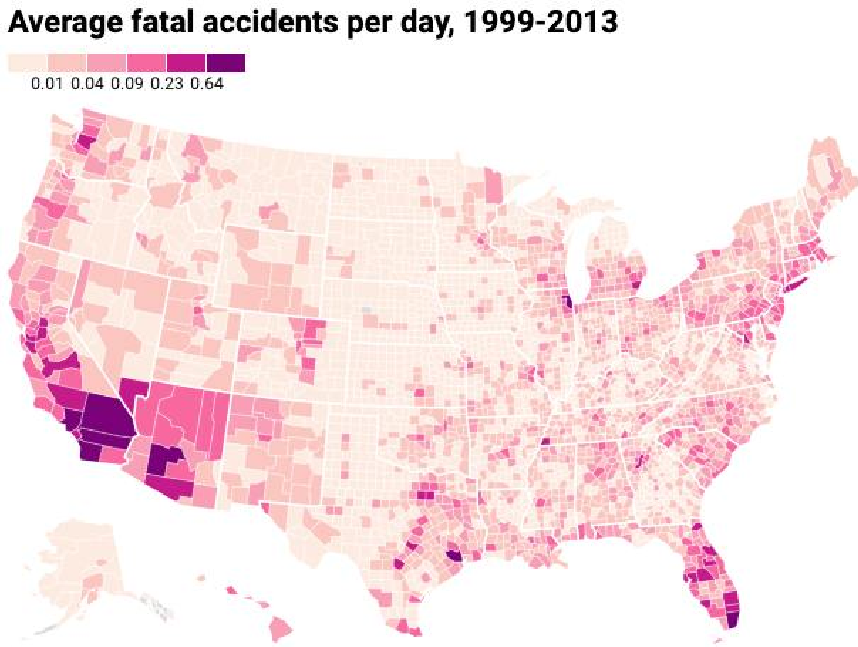


Figure 8: **San Francisco: daily $PM_{2.5}$ concentrations and wind direction.** This figure shows first stage results for San Francisco area, with dependent variable being $PM_{2.5}$ levels, and independent variable being wind direction. Control variables and fixed effects are accounted for. Results are consistent with what is expected - if the wind blows from South-East (continental), recorded air quality is low, and if the wind blows from the West (the ocean), recorded air quality is high.


Average fatal accidents per day, 1999-2013
0.01 0.04 0.09 0.23 0.64

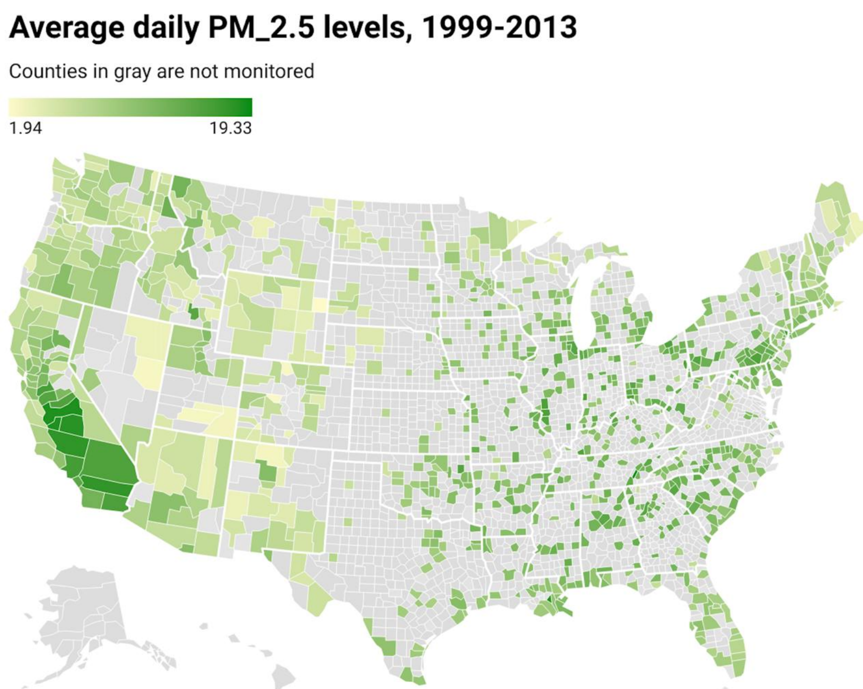

Average daily PM_2.5 levels, 1999-2013
Counties in gray are not monitored
1.94
19.33

Figure 9

Variable	Mean	Std. Dev.	Observations
Fatal crash	0.067	0.00013	4542124
$PM_{2.5}$ $\mu g/m^3$	10.6	7.14	4548823
tmax (F)	119.5	10.63	4548823
tmin (F)	107.18	9.84	4548823
Wind Speed (mtrs/sec)	4.49	2.87	4548823
Precipitation	4.5	2.87	4548823

Table 1: Summary Statistics

Table 2: OLS Regression Results using Daily Data

	Dependent Variable: Total Car Crashes	
	(1)	(2)
$PM_{2.5}$	0.0002***	0.0001***
	(0.00003)	(0.00003)
Observations	4548815	4548815
Controls	×	✓
Fixed Effects	×	✓

Note: Results are based on daily-level data for the US. The dependent variable is the total number of fatal car crashes per day. Column (1) presents the baseline OLS regression without controls or fixed effects. Column (2) includes additional weather-related controls and fixed effects. Standard errors are clustered at the county level, and all regressions are weighted by the county population. Significance levels are denoted by $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table 3: OLS Regression Results using hourly data

	Dependent Variable: Fatal Car Crashes	
	(1)	(2)
$PM_{2.5}$	0.000018^{***}	0.000009^{***}
	(0.000003)	(0.000003)
Observations	5,091,589	5,091,589
Residual Std. Error	0.0603 (df = 5,091,588)	0.0603 (df = 5,091,588)
F Statistic	37.00^{***} (df = 1; 5,091,588)	52.30^{***} (df = 2; 5,091,588)
Controls	✗	✓
Fixed Effects	✗	✓

Note: Results in this table are based on hourly-level data for the US for the period 2010-2013. The dependent variable is the number of fatal car crashes per hour. Column (1) presents the baseline OLS regression without controls or fixed effects. Column (2) includes additional weather-related controls and fixed effects. Standard errors are clustered at the county level, and all regressions are weighted by the county population. Significance levels are denoted by *p < 0.1; **p < 0.05; ***p < 0.01.

Table 4: The Effect of $PM_{2.5}$ on Fatal Car Crashes: IV Estimates at Daily Level

	Dependent Variable: Fatal Car Crashes		
	(1)	(2)	(3)
$PM_{2.5}$	0.003639***	0.000895***	0.000905***
	(0.000189)	(0.000023)	(0.000023)
Precipitation		-0.00260***	-0.00260***
		(0.00005)	(0.00005)
Wind Speed		-0.00006	-0.00005
		(0.00005)	(0.00005)
County FE	✗	✓	✓
State-Month FE	✗	✓	✓
Month-Year FE	✗	✓	✓
Day-of-Week FE	✗	✗	✓
Mean of Crashes	0.067	0.067	0.067
% Effect	5.43%	1.34%	1.35%
Observations	4,548,815	4,548,815	4,548,814
Residual Std. Error	0.3305	0.2854	0.2852
F Statistic	370.5***	2,940***	3,044***

Note: Results in this table are based on daily-level data for the U.S. The dependent variable is the number of fatal car crashes per day. Column (1) presents the baseline IV regression without controls or fixed effects. Column (2) adds controls for weather conditions and temperature, along with County, State-Month, and Month-Year fixed effects. Column (3) adds Day-of-Week fixed effects to account for variations in driving patterns across days. Each coefficient represents the effect of a 1 µg/m³ increase in $PM_{2.5}$ on fatal crashes. The percentage effects are calculated relative to the mean number of crashes (0.067 per day). Standard errors are clustered at the county level. Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01.

Table 5: The Effect of $PM_{2.5}$ on Fatal Car Crashes: IV Estimates at hourly level

	Dependent Variable: Fatal Car Crashes		
	(1)	(2)	(3)
$PM_{2.5}$	0.000265***	0.000016*	0.000071***
	(0.000034)	(0.000010)	(0.000009)
Precipitation		-0.0002***	-0.000152***
		(0.00001)	(0.000009)
Wind Speed		-0.0001***	-0.000081***
		(0.00001)	(0.00001)
County FE	✗	✓	✓
State-Month FE	✗	✓	✓
Month-Year FE	✗	✓	✓
Day-of-Week FE	✗	✗	✓
Mean of Crashes	0.0036	0.0036	0.0036
% Effect	7.36%	0.44%	1.97%
Observations	5,091,589	5,091,589	5,091,589
Residual Std. Error	0.0603	0.0603	0.06026
F Statistic	59.91***	192.50***	374.3***

Note: Results in this table are using hourly-level data for the US for the period 2010-2013. The dependent variable is the number of fatal car crashes per hour. Column (1) presents the baseline IV regression without any controls or fixed effects. Column (2) includes additional controls for weather conditions and temperature, along with County, State-Month, and Month-Year FE. Column (3) adds Day-of-Week fixed effects to account for variation in driving patterns across different days of the week. Each coefficient represents the effect of a 1 µg/m^3 increase in $PM_{2.5}$ on fatal crashes. The percentage effects are calculated relative to the mean number of crashes (0.0036 per hour). Standard errors are clustered at the county level, and all regressions are weighted by the county population. Significance levels are denoted by *p < 0.1, **p < 0.05, ***p < 0.01*.

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