Does Air Pollution Affect the Likelihood of a Car Crash? Evidence from the US

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Abstract

This paper examines the causal impact of fine particulate matter ($PM_{2.5}$) on traffic crashes using instrumental variable analysis with wind direction as an instrument for air pollution. I provide evidence at both the national level across U.S. counties and through a detailed case study of Chicago. The national analysis reveals that a 1 $\mu g/m^3$ increase in daily $PM_{2.5}$ levels leads to a 1.34% increase in fatal accidents after accounting for weather conditions and fixed effects. Extending to hourly data, I find that a 1 $\mu g/m^3$ increase in $PM_{2.5}$ in the hour prior to an accident results in a 1.97% increase in fatal crashes, indicating that immediate pollution exposure impairs cognitive function in real time. The Chicago case study validates these findings while revealing that pollution affects crash severity, suggesting pollution impairs drivers' ability to avoid or mitigate severe outcomes. Individual crash-level analysis confirms that $PM_{2.5}$ increases injury severity conditional on a crash occurring. A one unit reduction in $PM_{2.5}$ could prevent approximately 550 fatal crashes annually nationwide, valued at \$4.06 billion using the EPA's Value of Statistical Life. These findings contribute to the literature on the cognitive effects of air pollution and suggest that the social costs of pollution may be underestimated.

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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^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^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^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.

To validate and extend the national findings, I conduct a detailed case study of Chicago from 2017 to 2025. The Chicago analysis offers several methodological advantages that enhance our understanding of the pollution-crash relationship. First, Chicago provides a controlled urban setting where monitoring infrastructure is more comprehensive and consistent than in many counties, reducing measurement error in pollution exposure. Second, the city's detailed crash reporting system captures individual-level information on crash severity, road conditions, lighting, and weather that is unavailable in the national FARS database. Third, examining a single metropolitan area allows me to better control for local factors such as traffic patterns, infrastructure quality, and enforcement policies that might confound the relationship between pollution and crashes at broader geographic scales.

The Chicago case study reveals important findings beyond crash frequency.

Using individual crash-level data, I demonstrate that air pollution not only increases the number of crashes but also affects their severity. An ordered logit analysis shows that conditional on a crash occurring, higher $PM_{2.5}$ concentrations significantly increase the probability of more severe injuries. This finding suggests that pollution impairs drivers' cognitive function in ways that prevent them from taking evasive action or mitigating collision impact. The instrumental variable estimates for Chicago show that a 1 µg/m^3 increase in $PM_{2.5}$ leads to a 0.78% increase in total crashes but a substantially larger 9.05% increase in fatal crashes. This disproportionate effect on fatal crashes reinforces the mechanism of cognitive impairment: pollution affects not just whether crashes occur, but drivers' ability to avoid the most severe outcomes in high-stakes moments requiring split-second decisions.

The Chicago results also provide validation of the national findings using a different data source and geographic scale. The consistency between the national county-level analysis and the Chicago city-level analysis strengthens confidence in the core findings and demonstrates that the pollution-crash relationship is robust across different levels of aggregation and urban contexts. Moreover, the availability of detailed crash-level data in Chicago enables investigation of how pollution interacts with other environmental and temporal factors—such as lighting conditions, road surface quality, and traffic patterns—to affect driving safety in ways that cannot be examined with the national FARS data alone.

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, $\mathrm{PM}_{2.5}$ 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. Sager (2019) 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 and by providing a detailed case study that examines not only crash frequency but also crash severity at the individual crash level. This more granular approach illustrates how fluctuations in pollution within a single day influence driving safety and demonstrates that pollution's effects extend beyond increasing crash likelihood to impairing drivers' ability to avoid or mitigate severe outcomes.

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. Section 7 presents the Chicago case study, including analysis of crash severity determinants and the effects of pollution on both crash frequency and severity. Finally, Section 8 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 2 and 5 show the change of fine particulate matter levels over time in the United States over the 1999-2013 time period. 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^3 in July. After this summer high, the concentration drops again, hitting its lowest point of the year—just over 9 μg/m^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 4 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

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

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/m³ 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 µg/m^3 to 8.1 µg/m^3 (Figure 5). This decline could translate to significant reductions in fatal car accidents. With my findings showing that a 1 µg/m^3 increase in $\mathrm{PM}_{2.5}$ leads to a 1.34% increase in daily accidents, a 5.5 µg/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 $\mathrm{PM}_{2.5}$ 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 $\mathrm{PM}_{2.5}$ coefficient remains significant.

The coefficient on $PM_{2.5}$ in Column (3) suggests that a 1 μg/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 Case Study: Chicago

The national-level analysis presented in previous sections establishes a robust causal relationship between $PM_{2.5}$ exposure and fatal car crashes across the United States. However, aggregating data at the county level, while necessary for achieving sufficient statistical power and geographic coverage, may mask important heterogeneity in how pollution affects traffic safety across different urban environments. Moreover, the county-level approach limits our ability to examine fine-grained patterns in crash timing, location, and severity that could shed light on the mechanisms through which pollution impairs driving behavior.

To address these limitations and provide complementary evidence, I now turn to a detailed case study of Chicago. This city-level analysis offers several advantages that enhance our understanding of the pollution-crash relationship. First, Chicago provides a controlled urban setting where monitoring infrastructure is more comprehensive and consistent than in many counties, reducing measurement error in pollution exposure. Second, the city's detailed crash reporting system captures individual-level information on crash severity, road conditions, lighting, and weather that is unavailable in the national FARS database. Third, examining a single metropolitan area allows me to better control for local factors such as traffic patterns, infrastructure quality, and enforcement policies that might confound the relationship between pollution and crashes at broader geographic scales.

The Chicago analysis serves three main purposes. First, it provides a validation of the main findings using a different data source and geographic unit of analysis. Second, it allows me to decompose the pollution effect by examining not just whether crashes occur, but how severe they are when they do occur. Third, the granular nature of Chicago's crash data enables investigation of how pollution interacts with other environmental and temporal factors to affect driving safety.

The following sections present descriptive statistics for Chicago, analyze the determinants of crash severity using individual crash-level data, and estimate the causal effect of $PM_{2.5}$ on both crash frequency and severity using an instrumental variables approach analogous to the national analysis. Importantly, the Chicago results extend the main findings, demonstrating that the pollution-crash relationship is robust across different levels of aggregation and revealing new insights about how air quality affects the severity of traffic accidents.

8 Data

The Chicago dataset integrates three primary data sources: individual-level traffic crash records, air pollution measurements, and meteorological conditions. This allows for a comprehensive analysis of how air quality affects both the frequency and severity of motor vehicle crashes in an urban setting.

Traffic Crash Data. Crash information comes from the Chicago Data Portal, maintained by the City of Chicago Department of Transportation. The data include every reported motor vehicle crash within city limits from 2017 through 2025, providing a complete census of traffic incidents during this period. Each crash record contains detailed information on the date, time, and precise location of the incident, along with injury severity classifications for all involved parties and contributing factors such as weather conditions, road surface quality, lighting, and posted speed limits. This granular detail allows analysis of both crash frequency and severity, as well as how pollution interacts with other environmental and road conditions.

Air Quality Data. Air pollution measurements are obtained from the U.S. Environmental Protection Agency's Air Quality System (EPA AQS), which maintains a network of monitoring stations throughout the United States. I use hourly $PM_{2.5}$ measurements from all monitors within Cook County and the surrounding collar counties (DuPage, Kane, Lake, McHenry, and Will). $PM_{2.5}$ concentrations are measured in micrograms per cubic meter ($\mu g/m^3$). When multiple monitors report data for the same hour, I calculate the arithmetic mean across all available monitors to obtain a single representative measure of air quality for the Chicago area. This averaging approach reduces measurement error from individual monitor readings and provides a more accurate representation of ambient air quality experienced by drivers throughout the city. For descriptive purposes, I also compute the corresponding Air Quality Index (AQI), which translates $PM_{2.5}$ concentrations into a standardized scale used by public health agencies.

Meteorological Data. Weather data are obtained from the North American Regional Reanalysis (NARR), which provides comprehensive atmospheric information at high spatial and temporal resolution. Key meteorological variables include wind direction (measured in degrees), wind speed (meters per second), temperature (degrees Celsius), and precipitation intensity (millimeters per hour). Wind direction is defined as the direction from which the wind is blowing, for example, a southwest wind blows from the southwest toward the northeast. These weather variables serve two purposes: they act as control variables in the crash analysis to account for hazardous driving conditions, and wind direction serves as the instrumental variable for identifying the causal effect of pollution on crashes.

Spatial Matching. Weather and air quality measurements are spatially matched to the city of Chicago by selecting monitors and weather stations located within Cook County or within 20 kilometers of the city border. This geographic restriction ensures that the environmental measurements reflect conditions experienced by Chicago drivers. When multiple monitors or stations are available for a given time period, observations are averaged to obtain a single representative value.

Sample. The analysis excludes observations from 2020 and 2021 due to the substantial disruption in traffic patterns caused by the COVID-19 pandemic and associated lockdown measures. Including these years would introduce confounding variation in crash patterns unrelated to air quality. The final dataset contains 2,922 daily observations and 950,788 individual crash records over the study period.

9 Descriptive Statistics

Table 13 presents summary statistics for daily observations of traffic crashes, weather conditions, and air pollution levels in Chicago from 2017 through 2025 (excluding 2020-2021). The data reveal substantial variation in all key variables, providing the necessary variation to identify the effects of air pollution on traffic safety.

9.1 Traffic Crashes

The primary outcome of interest is the daily number of traffic crashes in Chicago. On average, the city experiences 291.77 total crashes per day, with a standard deviation of 63.95. This high baseline reflects Chicago's size, population density, and traffic volume. The distribution exhibits a right skew with occasional spikes exceeding 500 crashes per day. These extreme values typically correspond to severe weather events, holiday travel periods, or major traffic disruptions.

The vast majority of crashes result in no injury or minor injuries. Fatal crashes are rare, averaging just 0.33 per day (standard deviation of 0.60). This indicates that most days see no fatal crashes, which is consistent with urban driving patterns where lower speeds and congestion reduce the likelihood of high-severity collisions. Over the entire study period, Chicago recorded 1,024 fatal crashes, representing approximately 0.11% of all reported incidents.

Figure 11 displays the time series of daily crashes, revealing several important patterns. First, crash counts exhibit an upward trend from 2017 through early 2019, stabilizing around 300 crashes per day. Second, the onset of the COVID-19 pandemic in March 2020 produces a dramatic decline in crashes as lockdown measures reduced traffic volume. Following the relaxation of restrictions, crash counts gradually recovered but stabilized at levels slightly below the pre-pandemic baseline. The series also displays clear seasonality and occasional pronounced spikes attributable to weather events or holidays. Despite year-to-year fluctuations, there is no evidence of a long-term declining trend in crash risk.

Seasonal patterns are shown in Figure 12, which plots average monthly crash counts. Winter months (January and February) see the lowest crash rates, averaging around 270 crashes per day. Crash frequency increases steadily through spring and summer, peaking in September and October at over 320 crashes per day before declining again in November and December. This seasonal variation likely reflects multiple factors: reduced travel and more cautious driving during winter weather, increased recreational and vacation travel during summer months, and higher traffic congestion during fall.

The temporal distribution of crashes within days and across the week provides additional insights into driving patterns. Figure 13 shows that crashes follow a pronounced diurnal cycle, with minimal activity between 02:00 and 05:00 when traffic volume is lowest. Crash frequency rises sharply after 06:00, reaching a morning peak around 08:00 that coincides with the morning commute. A second, larger peak occurs between 16:00 and 19:00 during the evening rush hour, when traffic volume and congestion are highest. After 20:00, crash frequency declines steadily as traffic dissipates. This pattern closely tracks daily traffic flow, with crashes concentrated during periods of high vehicle volume and driver interaction.

Figure 14 presents the weekly distribution of crashes. Sunday consistently records the lowest crash counts, reflecting reduced weekday commuting and commercial traffic. Crash frequency increases progressively from Monday through Thursday, with peak counts occurring on Thursday and Friday as pre-weekend traffic intensifies. Saturday sees a slight decline from Friday but remains elevated relative to Sunday. This weekly pattern reflects the concentration of commuter travel and economic activity on weekdays, particularly toward the end of the work week.

9.2 Air Pollution

Chicago's air quality over the study period is characterized by moderate pollution levels with substantial day-to-day variation. Average daily $PM_{2.5}$ concentration is 9.18 μg/m^3, with a standard deviation of 4.66 μg/m^3. The corresponding Air Quality Index (AQI) averages 44.95, indicating that Chicago typically experiences air quality in the "Good" to "Moderate" range according to EPA classifications. However, considerable variation exists: $PM_{2.5}$ concentrations range from a minimum of 0.40 μg/m^3 to a maximum of 81.00 μg/m^3, with the extreme value occurring during the June 2023 Canadian wildfire episode that affected large portions of the Midwest and produced hazardous air quality across multiple states.

Figure 15 shows average $PM_{2.5}$ concentrations by month, revealing a bimodal seasonal pattern. The highest pollution levels occur in December and June, with monthly averages around 10 μg/m^3. The lowest concentrations appear in

September and October, falling below 9 μg/m^3. The winter peak likely reflects increased heating emissions and meteorological conditions that trap pollutants near the surface, while the summer peak corresponds to photochemical smog formation during hot weather and increased driving. The relatively clean air in early fall coincides with moderate temperatures that reduce both heating and cooling energy demand.

Figure 16 displays daily $PM_{2.5}$ concentrations over time. The series exhibits high-frequency variation, with levels typically ranging between 5 and 15 μg/m^3. Multiple short-duration spikes exceed 30 μg/m^3, often corresponding to weather patterns that trap pollutants or transport pollution from distant sources. The extreme outlier in June 2023, reaching over 80 μg/m^3, clearly stands out and aligns precisely with the Canadian wildfire smoke events. Importantly, it shows no clear downward trend in pollution levels over the study period, suggesting that average air quality remained relatively stable despite ongoing regulatory efforts.

9.3 Weather Conditions

Weather variables display the expected patterns for a Midwestern urban area. Average daily wind direction is approximately 177°, indicating predominantly southerly winds, with a standard deviation of 70° reflecting substantial directional variation. This variation in wind direction provides the identifying variation for the instrumental variables strategy, as different wind directions transport pollution from different source areas and determine local air quality. Average wind speed is 2.72 m/s, ranging from 0.58 to 44.83 m/s, with higher speeds typically associated with storm systems.

Precipitation is infrequent, with most days recording little to no rainfall. The distribution is highly right-skewed, with occasional extreme precipitation events. Temperature varies substantially across seasons, ranging from a minimum of -25.87°C during winter cold snaps to a maximum of 31.71°C during summer heat waves, with a mean of 12.63°C.

These weather variables serve dual purposes in the analysis. First, they act as important control variables because hazardous weather directly affects crash risk through reduced visibility, slippery road surfaces, and altered driver behavior. Second, wind direction serves as the instrumental variable that provides exogenous variation in $PM_{2.5}$ concentrations, allowing identification of the causal effect of air pollution on crashes. The substantial variation in wind patterns, combined with Chicago's geographic position relative to pollution sources, creates the necessary conditions for a strong first-stage relationship between wind direction and local air quality.

10 Effects of Pollution on Crash Severity

Before examining the causal effect of air pollution on the number of traffic crashes, I first examine the determinants of crash severity using individual-level crash data. Understanding what factors contribute to more severe injuries provides context for interpreting the pollution effects and helps to identify potential mechanisms through which air pollution may affect crashes.

Table 6 presents summary statistics for crashes separated by injury severity. First, the vast majority of crashes result in no injury (85.8%), consistent with the majority of city collisions being low-speed. Fatal crashes are rare, representing only 0.11% of all incidents, or approximately 1,024 fatalities over the sample period. Other categories include reported but not evident injuries (4.5%), non-incapacitating injuries (7.9%), and incapacitating injuries (1.6%).

Table 7 provides additional context by showing the distribution of weather and lighting conditions across all crashes. The data shows that most crashes occur under favorable conditions: 78.4% happen in clear weather and 64.1% in daylight.

To examine how these and other factors systematically affect crash outcomes, I estimate an ordered logit model. This approach is appropriate given that injury severity is naturally ordered from least to most severe: no injury, reported injury, non-incapacitating injury, incapacitating injury, and fatal. The ordered logit coefficients represent log odds ratios, where a positive coefficient indicates that an increase in the predictor raises the probability of more severe injury.

Table 8 presents the ordered logit results. Posted speed limits have a positive and significant relationship with injury severity across all specifications. In the baseline model (Column 1), each additional mile per hour of posted speed limit increases the log odds of more severe injury by 0.046. This coefficient remains stable when environmental controls are added (0.043 in Columns 2 and 3), with t-statistics exceeding 59 in all specifications. It indicates that each 1 mph increase in posted speed raises the odds of being in a higher severity category by 4.4%.

Lighting conditions also have effects on crash severity. Relative to daylight crashes, those that occur on dark but lighted roads show substantially higher severity, with a coefficient of 0.313, meaning crashes on dark, lighted roads have 37% higher odds of more severe injury compared to daylight crashes. Dawn and dusk periods also show increased severity, with coefficients of 0.180 and 0.121 respectively. Interestingly, crashes on unlighted dark roads show no significant difference from daylight crashes. This counterintuitive result may suggest that unlighted roads tend to be lower-speed residential streets where drivers exercise greater caution in darkness.

Weather conditions show a less straightforward pattern. Freezing rain exhibits the strongest effect, corresponding to an 18% increase in the chance of more severe injury. Severe weather conditions also show higher severity. These patterns are consistent with drivers potentially reducing speed and being cautious during obviously hazardous conditions like snow, but failing to adjust sufficiently for more subtle hazards like wet pavement or reduced visibility in rain.

Road surface conditions reinforce this interpretation. Wet surfaces increase crash severity, while ice or snow on the roadway shows a large negative coefficient, implying a 28% reduction in the odds of severe injury. This suggests that drivers respond more cautiously to visible ice and snow than to wet pavement, which may be less visibly apparent but still worsens vehicle handling.

The rush hour coefficient in Column (3) is negative and statistically significant. Crashes occurring during peak commute times (7–9am or 4–6pm) have 3.4% lower probability of severe injury compared to off-peak crashes. This finding aligns with the descriptive evidence showing that fatal crashes are disproportionately concentrated outside rush hours. Traffic congestion during peak periods likely constrains vehicle speed, reducing crash severity even as crash frequency may be higher due to increased traffic volume.

The ordered logit estimates show that crash severity is related to observable factors of the road environment. Higher speed, reduced lighting, certain weather conditions, and off-peak timing all contribute to more severe injuries conditional on a crash occurring. These findings provide a foundation for examining whether air pollution, through its documented effects on cognitive function, affects crash severity.

I now examine whether air pollution affects injury outcomes conditional on a crash occurring (Table 5). If PM2.5 impairs cognitive function, it might both increase crash likelihood and also affect drivers' ability to avoid or mitigate collisions, potentially leading to more severe injuries.

Table 5 presents ordered logit estimates examining the relationship between PM2.5 concentrations and crash severity. Column (1) reproduces the baseline specification from the previous section for comparison, excluding pollution measures. Column (2) adds daily average PM2.5 concentration. Column (3) adds year and month fixed effects to control for seasonal patterns.

The results show a small but statistically significant association between air pollution and crash severity when temporal fixed effects are included. In the specification without fixed effects (Column 2), the PM2.5 coefficient is small and statistically insignificant, but once year and month fixed effects are added in Column (3), the coefficient becomes significant. This suggests that the relationship between pollution and severity is confounded by seasonal factors. Both PM2.5 concentrations and crash severity show seasonal variation: pollution tends to be higher in winter and summer months due to heating and traffic patterns, while crash severity varies with seasonal changes in driving conditions and traffic.

The estimated coefficient in Column (3) implies that a 1 $\mu g/m^3$ increase in PM2.5 raises the odds of being in a more severe injury category by 0.3%. For a one standard deviation increase in PM2.5 (approximately 4.7 $\mu g/m^3$), the odds of more severe injury increase by about 1.4%. This effect is smaller than the effects of other environmental factors. For comparison, crashes occurring on dark but lighted roads have 39% higher odds of severe injury relative to daylight crashes, and crashes on wet surfaces have 19% higher odds compared to dry conditions.

11 Effects of Pollution on Crashes

The main empirical challenge in estimating the causal effect of air pollution on traffic crashes is that exposure to PM2.5 is not randomly assigned. Air pollution levels are correlated with various economic activities, traffic patterns, and weather conditions that independently affect crash risk. Moreover, pollution monitors may be strategically placed, and measured pollution at monitors may not represent true exposure for all drivers in the city. These issues introduce both measurement error and omitted variable bias in ordinary least squares (OLS) estimates. To address these concerns, I use an instrumental variables (IV) approach that exploits exogenous variation in daily wind direction. The key insight is that while wind direction affects local pollution concentrations by transporting pollutants from different source areas, wind direction itself does not directly affect driving behavior or crash risk when I control for wind speed and other weather conditions.

Let d index days and m denote month and y - year respectively. The relationship between crashes and fine particulate matter in Chicago is given by:

$$Y_{dmy} = \beta PM2.5_{dmy} + X'_{dmy}\gamma + \delta_w + \theta_{my} + \epsilon_{dmy}$$

The specification includes day-of-week fixed effects to account for systematic differences in traffic patterns and driving behavior across weekdays and weekends, and month-by-year fixed effects to control for seasonal variation in both crashes and pollution, as well as year-to-year trends. These month-by-year fixed effects are particularly important given that the sample excludes 2020 and 2021 due to the COVID-19 pandemic's effects on traffic patterns. With daily aggregation, I cannot include day fixed effects, but control for temporal patterns through month-by-year and day-of-week fixed effects.

The identifying assumption for the IV approach is that conditional on weather controls and fixed effects, daily wind direction affects crashes only through its impact on air pollution. This assumption is plausible because wind direction determines which pollution sources contribute to local concentrations, but wind direction itself, holding wind speed constant, does not directly affect driving conditions or behavior. I construct instruments by dividing wind direction into discrete bins. Following the approach in Deryugina et al. (2019), I create indicator variables for wind direction bins, with one bin serving as the omitted reference category.

$$PM2.5_{dmy} = \sum_{b \in B} \alpha_b \mathbb{1}[WindDir_{dmy} = b] + X'_{dmy}\pi + \delta_w + \theta_{my} + u_{dmy}$$

I focus on a 4-bin specification with 90° bins (North-Northeast [0°-90°), East-Southeast [90°-180°), South-Southwest [180°-270°), and West-Northwest [270°-360°)). The West-Northwest direction serves as the reference category, as winds from this direction bring cleaner air from Lake Michigan and rural areas to the west. This specification uses three instruments (four bins minus the reference category).

This IV strategy requires that wind direction bins are strong predictors of pollution levels and that they satisfy the exclusion restriction. The first-stage F-statistic tests instrument strength.

Geographic context: Chicago's pollution sources are not uniformly distributed. Industrial facilities and major highways are concentrated to the south and southwest of the city center, while Lake Michigan lies to the east and northeast. Consequently, southerly and southwesterly winds tend to bring higher PM2.5 concentrations, while easterly and northerly winds from the lake bring cleaner air. This geographic variation provides the identifying variation exploited by the IV strategy.

11.1 First Stage Results

Figure 10 shows the first stage relationship between wind direction and PM2.5 concentrations. The pattern is clear: winds from the east (E) and southeast (SE) are associated with PM2.5 concentrations above 10 $\mu g/m^3$, while winds from the northwest (NW) are associated with concentrations around 5 $\mu g/m^3$. This substantial variation across wind directions provides strong predictive power for the instrumental variables approach.

11.2 OLS Results

Table 10 presents OLS estimates of the effect of PM2.5 on daily crashes. The OLS coefficient on PM2.5 is negative but statistically insignificant across all three outcomes (total crashes, fatal crashes, and non-fatal crashes). The weather controls show expected patterns: precipitation intensity is strongly positively associated with crashes (10.1 additional total crashes per unit increase in rain intensity), consistent with rain creating hazardous driving conditions. Wind speed is negatively associated with total and non-fatal crashes (2.2 fewer crashes per m/s increase in wind speed), potentially reflecting reduced travel during high-wind conditions. Wind speed also shows a negative relationship with fatal crashes, though the magnitude is much smaller (0.020 fewer fatal crashes per m/s). The statistically insignificant OLS coefficients on PM2.5 suggest that OLS fails to capture the true effect of air pollution on crashes. This is consistent with measurement error attenuating OLS estimates toward zero, as pollution monitors may not accurately capture exposure for all drivers throughout the city.

11.3 IV Results

Table 11 presents the main IV results using four 90° wind direction bins as instruments. The IV estimates are dramatically different from OLS, both in magnitude and statistical significance. A 1 $\mu g/m^3$ increase in PM2.5 leads to 2.314 additional total crashes per day ($p < 0.05$) and 0.028 additional fatal crashes per day ($p < 0.05$). The effect on non-fatal crashes is nearly identical to total crashes (2.300 additional crashes), as expected given that fatal crashes are a small fraction of total crashes.

Relative to the sample means, these effects represent a 0.78% increase in total crashes and a 9.05% increase in fatal crashes per 1 $\mu g/m^3$ increase in PM2.5. The much larger percentage effect for fatal crashes suggests that air pollution has a disproportionate impact on crash severity, not just crash frequency.

The first-stage F-statistic is 37.8, exceeding the Stock-Yogo critical value of 22.3 for 10% maximal IV size with three instruments, indicating that wind direction bins are strong predictors of PM2.5 concentrations and that the IV estimates are reliable.

Given Chicago's mean PM2.5 concentration of 9.18 $\mu g/m^3$ with a standard deviation of 4.66 $\mu g/m^3$, a one standard deviation increase in pollution would lead to approximately 10.8 additional total crashes and 0.13 additional fatal crashes per day. Over a year, this translates to roughly 47 additional fatalities attributable to one standard deviation higher pollution, a substantial public health burden.

Table 12 presents results using eight 45° wind direction bins as a robustness check. The 8-bin specification yields qualitatively similar but slightly smaller estimates: a 1 $\mu g/m^3$ increase in PM2.5 leads to 1.600 additional total crashes ($p < 0.10$) and 0.020 additional fatal crashes ($p < 0.10$). These translate to percentage effects of 0.54% for total crashes and 6.46% for fatal crashes. However, the 8-bin specification produces a weaker first-stage F-statistic of 17.6, which falls below the Stock-Yogo critical value of 22.3. This reduction in instrument strength adds both noise and potential bias to the estimates. Bias in 2SLS is proportional to the number of excluded instruments minus two, so the additional instruments in the 8-bin specification may introduce more bias than they reduce. For this reason, I focus on the 4-bin specification as my main result, though the consistency between the two specifications in terms of sign, magnitude, and the pattern of larger effects on fatal crashes provides reassurance that the findings are not driven by the specific choice of instruments.

11.4 Interpreting the Severity Effects

A key finding of this analysis is that air pollution has a larger percentage effect on fatal crashes (9% per $\mu g/m^3$ in the 4-bin specification) compared to total crashes (0.78% per $\mu g/m^3$). This differential effect suggests that PM2.5 exposure affects not only the likelihood of a crash occurring but also the severity of crashes that do occur. This finding connects directly to the ordered logit results in Table 5, which show that PM2.5 increases crash severity conditional on a crash occurring.

The ordered logit estimates indicate that a 1 $\mu g/m^3$ increase in PM2.5 increases the odds of being in a more severe injury category by 0.3%. When combined with an increase in the overall number of crashes, the result is a disproportionately large increase in fatal outcomes.

The mechanism linking pollution to crash severity likely operates through cognitive impairment. Previous research has established that PM2.5 exposure impairs cognitive function, including attention, reaction time, and decision-making. The crash severity analysis showed that factors requiring quick reactions, such as driving in darkness or at higher speeds, are strongly associated with more severe outcomes. If pollution impairs drivers' cognitive function, affected drivers may be less able to avoid crashes entirely (increasing crash frequency) and less able to take evasive action or mitigate impact when crashes occur (increasing crash severity).

Supporting this interpretation, the ordered logit results show that pollution's effect on severity only becomes significant when year and month fixed effects are included, highlighting the importance of controlling for seasonal confounders in both the individual-level severity analysis and the aggregate crash count analysis.

Several factors may explain why the Chicago estimates are substantial. First, Chicago is a dense urban environment with high traffic volume, where cognitive impairment may have larger consequences due to more complex driving conditions and greater interaction between vehicles. Second, the estimates here focus on a single city with relatively uniform monitoring, potentially reducing measurement error compared to county-level averages across diverse geographic areas.

12 Discussion

This paper examines how exposure to fine particulate matter ($PM_{2.5}$) affects traffic crashes, providing evidence at both the national and city level. Using instrumental variable approaches that exploit exogenous variation in wind direction, I estimate the causal effects of air pollution on traffic safety. The consistency of results across different data sources, levels of aggregation, and temporal scales strengthens confidence in the core finding: air pollution increases crash risk and severity through its effects on cognitive function.

12.1 Key Findings

The national analysis establishes that a 1 μg/m^3 increase in $PM_{2.5}$ leads to a 1.34% increase in daily fatal accidents. The hourly analysis reveals even stronger immediate effects: a 1.97% increase when controlling for day-of-week patterns. The Chicago case study validates these findings while revealing a crucial additional insight that pollution has disproportionate effects on crash severity. While total crashes increase by 0.78% per μg/m^3, fatal crashes increase by 9.05%, more than ten times the percentage effect. This pattern, combined with the ordered logit analysis showing pollution increases injury severity conditional on a crash occurring, suggests that pollution impairs not only the likelihood of crashes but also drivers' ability to avoid or mitigate severe outcomes.

12.2 Mechanisms

The combined evidence points to cognitive impairment as the primary mechanism. Prior research establishes that $PM_{2.5}$ exposure degrades attention, reaction time, decision-making, and executive function, which are all critical for safe driving. The finding that pollution has larger effects on fatal crashes provides particularly strong support: fatal crashes often result from failures in the precise moments when quick reactions could prevent a collision or reduce its severity. If pollution impairs these real-time responses, drivers would be both more likely to crash and less able to avoid the most severe outcomes.

The temporal patterns support this interpretation. The hourly analysis shows that immediate exposure has strong effects, consistent with short-term cognitive impacts. Effects also accumulate over the day, suggesting pollution's cognitive impacts build with exposure duration. The Chicago individual-level data reveal that pollution's effects are present across all driving conditions but would be particularly consequential in high-stakes situations involving high speeds, darkness, adverse weather, where cognitive function and quick reactions determine outcomes.

12.3 Policy Implications

These findings have substantial implications for environmental policy. Standard cost-benefit analyses of air quality regulations focus primarily on respiratory and cardiovascular health impacts. The traffic safety channel identified here represents an additional benefit stream that is currently undervalued in policy evaluation.

The economic magnitudes are significant. Using the national estimates, a one standard deviation reduction in $PM_{2.5}$ (4.7 μg/m^3) would prevent approximately 550 fatal crashes annually in monitored counties, valued at roughly \$4.06 billion using the EPA's Value of Statistical Life. The Chicago estimates imply similar magnitudes: a one standard deviation reduction would prevent approximately 47 fatalities per year, valued at $348 million. These figures represent only mortality costs and exclude non-fatal injuries, property damage, emergency response costs, and lost productivity, meaning the full economic burden is substantially higher.

Historical context illustrates the potential gains from pollution reduction. Between 1999 and 2013, $PM_{2.5}$ levels fell approximately 40%, which would correspond to a 7.4% reduction in fatal crashes—potentially thousands of lives saved annually. However, the Chicago data show pollution levels remained stable from 2017 to 2025, suggesting recent progress has stalled and substantial opportunities for further improvement remain.

Beyond traditional regulation, these findings suggest value in real-time interventions. Pollution forecasting could identify high-risk periods, enabling targeted warnings, temporary speed reductions, or increased enforcement during high pollution episodes. Areas with both high traffic volume and high pollution face compounded risks, suggesting that urban pollution reduction efforts may yield particularly high returns.

12.4 Conclusion

This paper provides comprehensive evidence that air pollution increases traffic crashes and fatalities through cognitive impairment. The national analysis establishes robust causal effects, while the Chicago case study validates these findings and reveals that pollution disproportionately increases the most severe crashes. The magnitudes are economically significant: modest reductions in $PM_{2.5}$ could prevent thousands of crashes and save billions of dollars annually.

Future research could examine heterogeneity across driver characteristics to identify vulnerable populations, investigate which crash types are most sensitive to pollution, combine pollution data with direct cognitive measures, and evaluate whether existing interventions like pollution alerts successfully reduce crash risk during high-pollution episodes.

These findings underscore that air pollution's social costs extend beyond respiratory and cardiovascular health to include traffic safety consequences. Environmental policies that reduce pollution generate benefits through multiple channels, and incorporating the traffic safety benefits identified here strengthens the case for stricter pollution control. More broadly, this research contributes to growing evidence that environmental conditions affect real-time cognitive performance in high-stakes settings, with important implications for public health and safety.

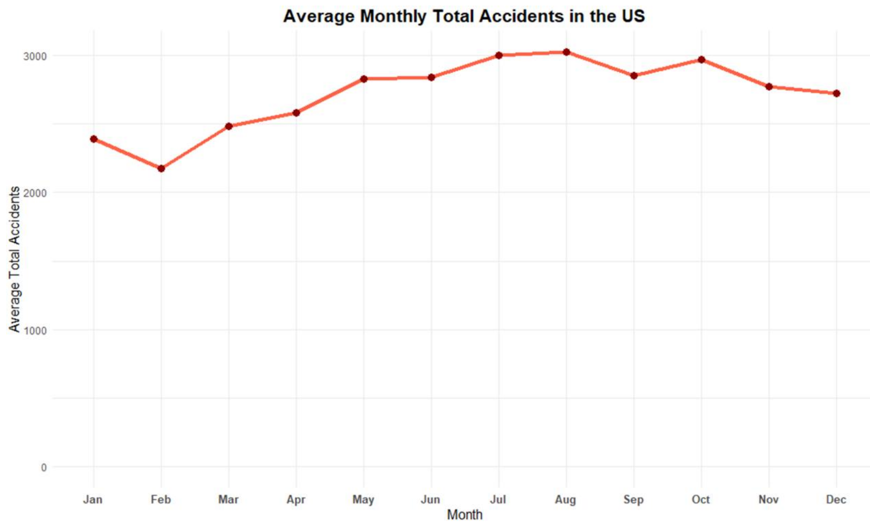

Figure 1: Average Monthly Total Accidents in the US

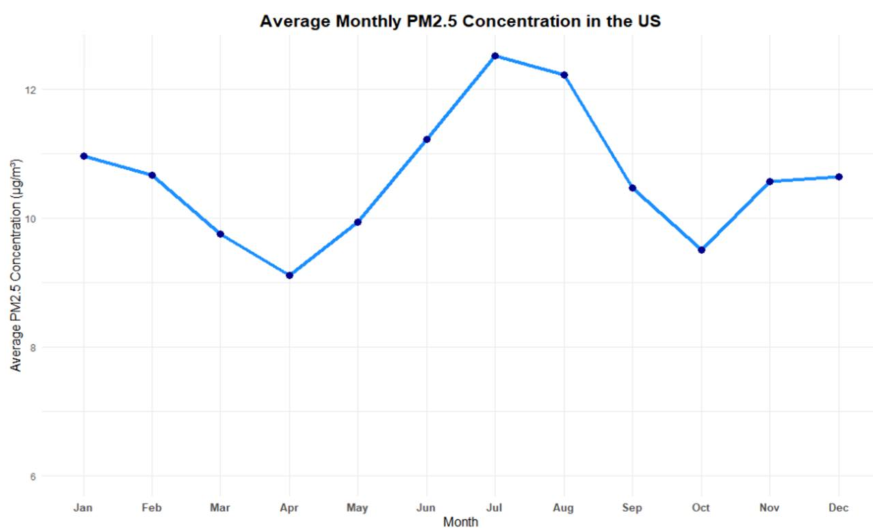

Figure 2: Average Monthly $PM_{2.5}$ Concentration in the US

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.

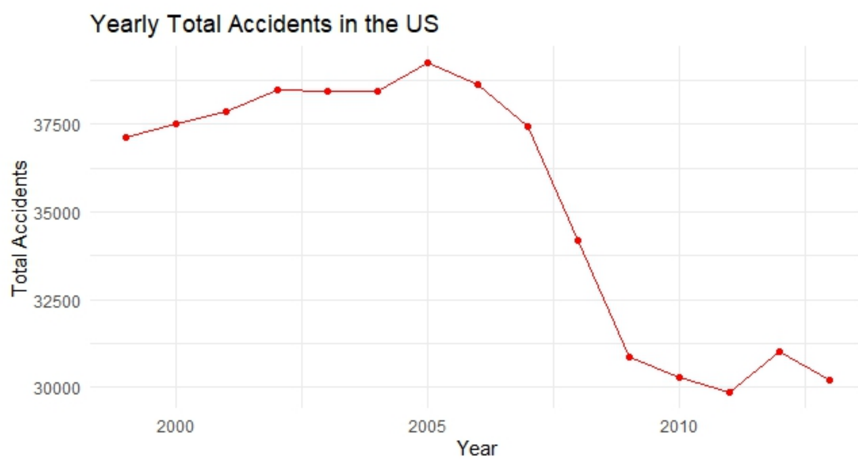

Figure 4: Average Yearly Total Accidents in the US

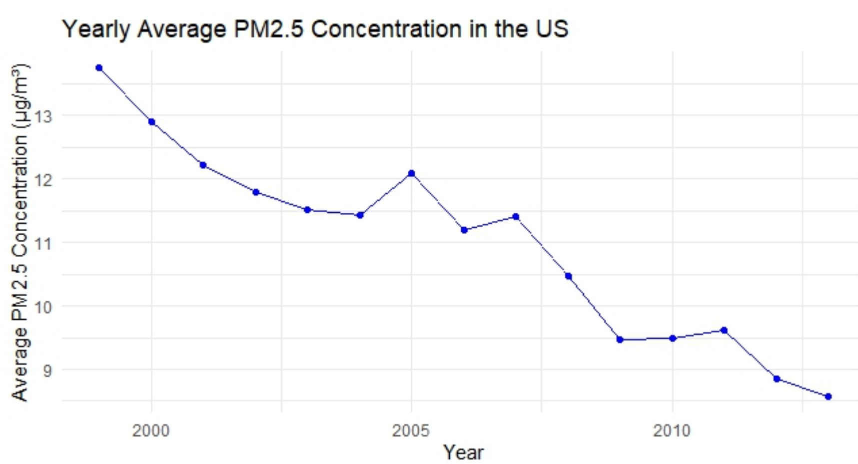

Figure 5: Average Yearly $PM_{2.5}$ Concentration in the US

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 $PM_{2.5}$.

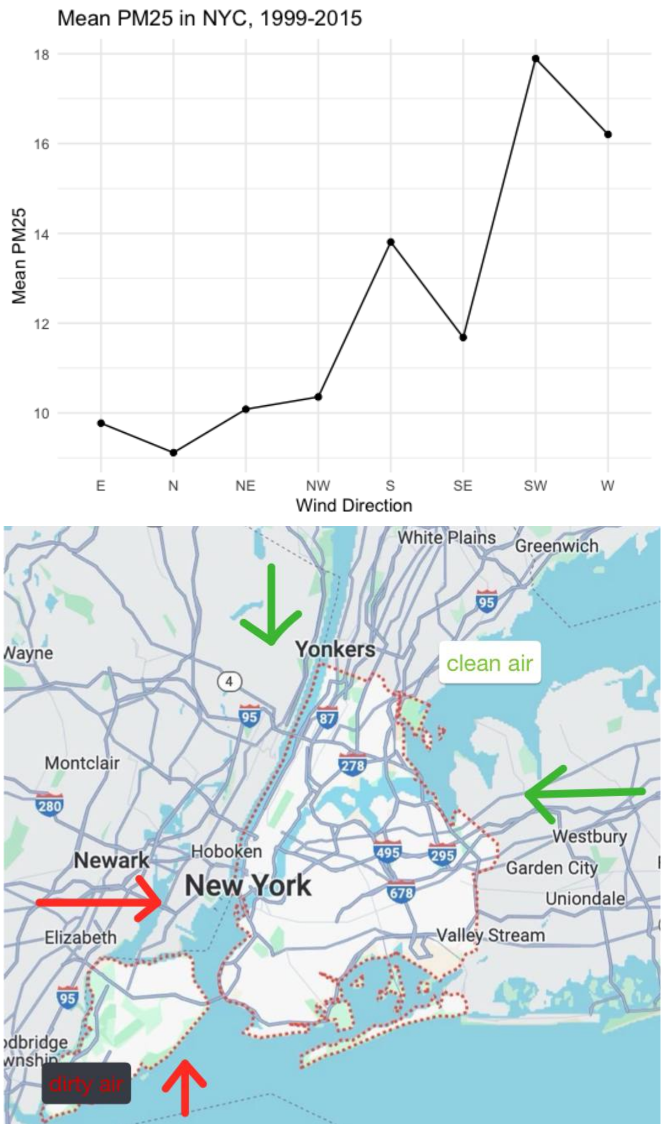

Figure 7: **New York City: daily $PM_{2.5}$ concentrations and wind direction.** This figure shows first stage results for New York City area, with dependent variable being $PM_{2.5}$ levels, and independent variable being wind direction. Control variables and fixed effects are accounted for. Results 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.

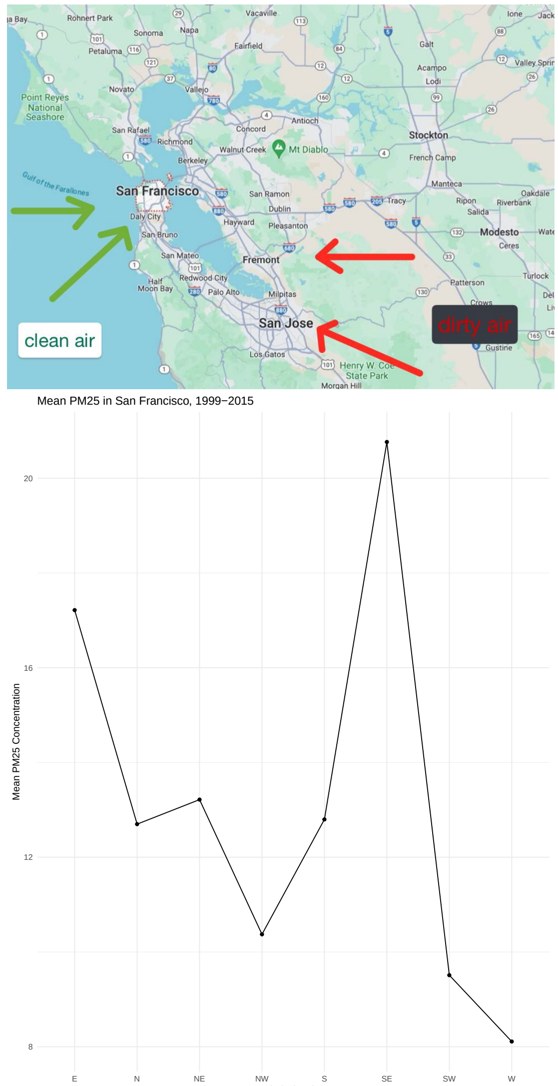

Figure 8: **San Francisco: daily $PM_{2.5}$ concentrations and wind direction.** This figure shows first stage results for San Francisco area, with dependent variable being $PM_{2.5}$ levels, and independent variable being wind direction. Control variables and fixed effects are accounted for. Results 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.

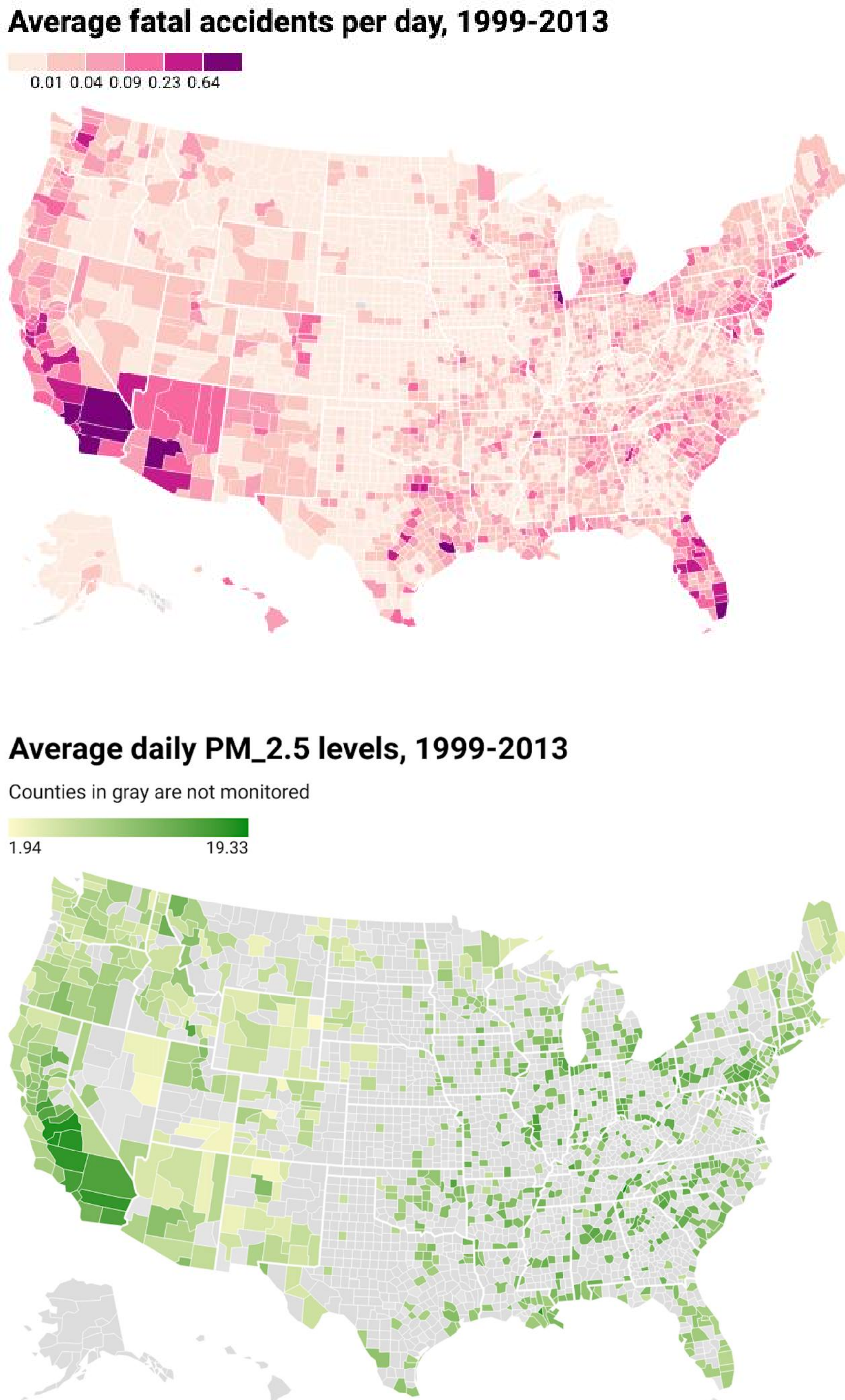
Average fatal accidents per day, 1999-2013
0.01 0.04 0.09 0.23 0.64
Average daily PM_2.5 levels, 1999-2013
Counties in gray are not monitored
1.94
19.33

Figure 9

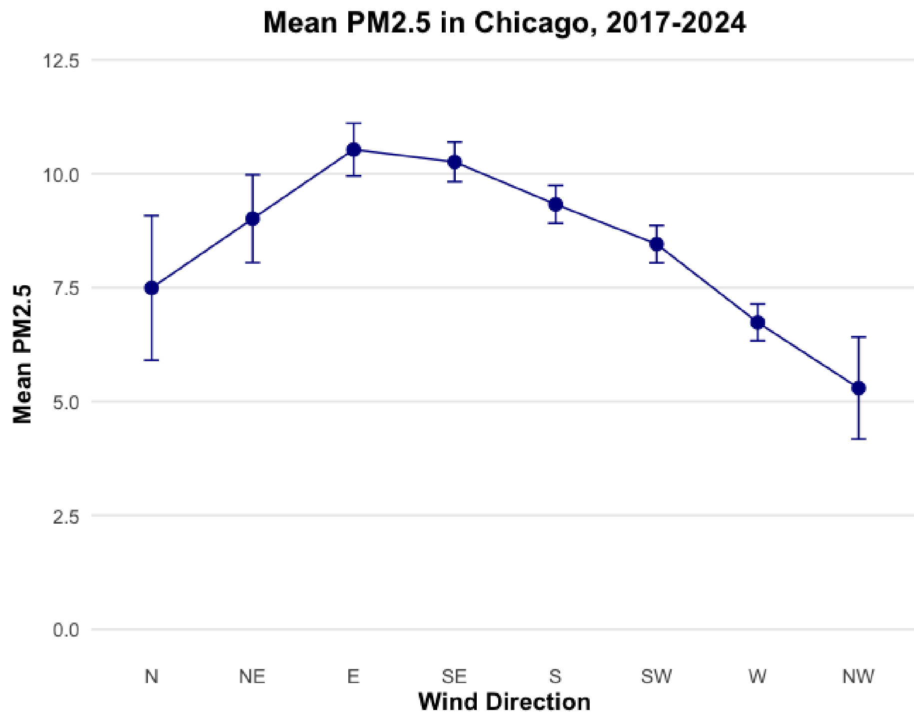

Figure 10: First Stage: Mean PM2.5 Concentration by Wind Direction

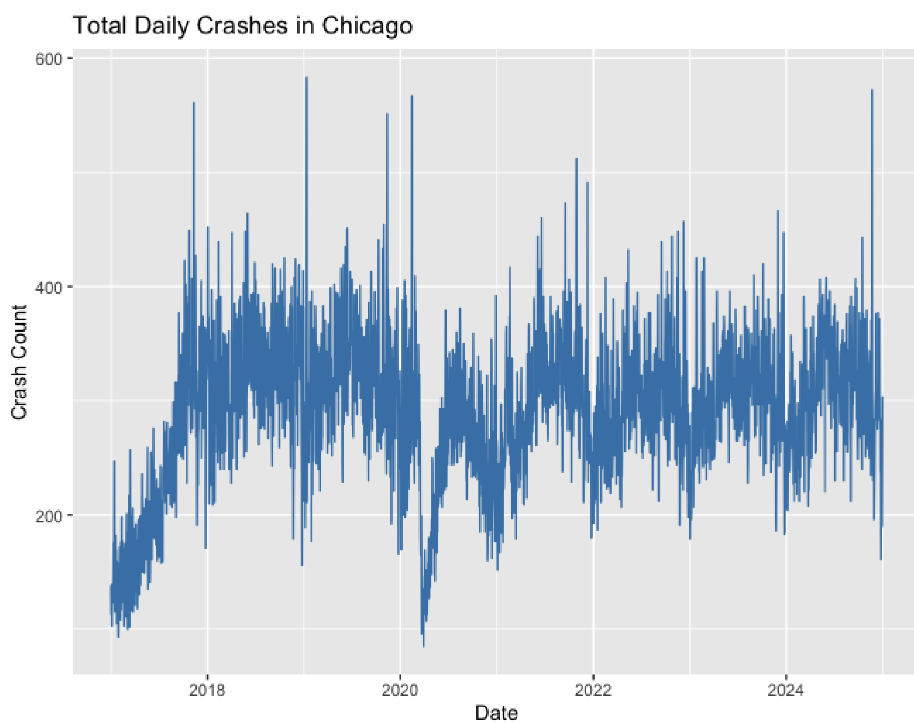

Figure 11: Total Daily Crashes in Chicago

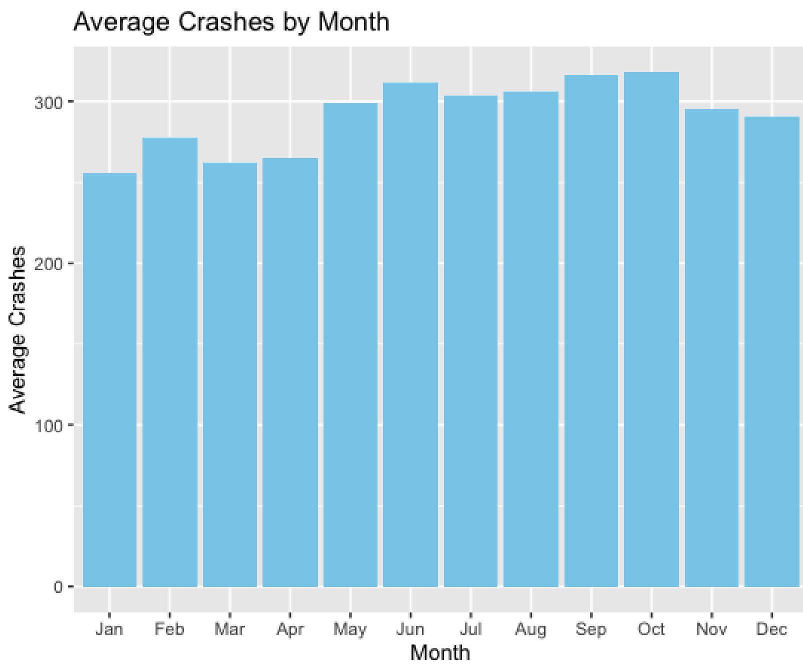

Figure 12: Average Crashes by Month

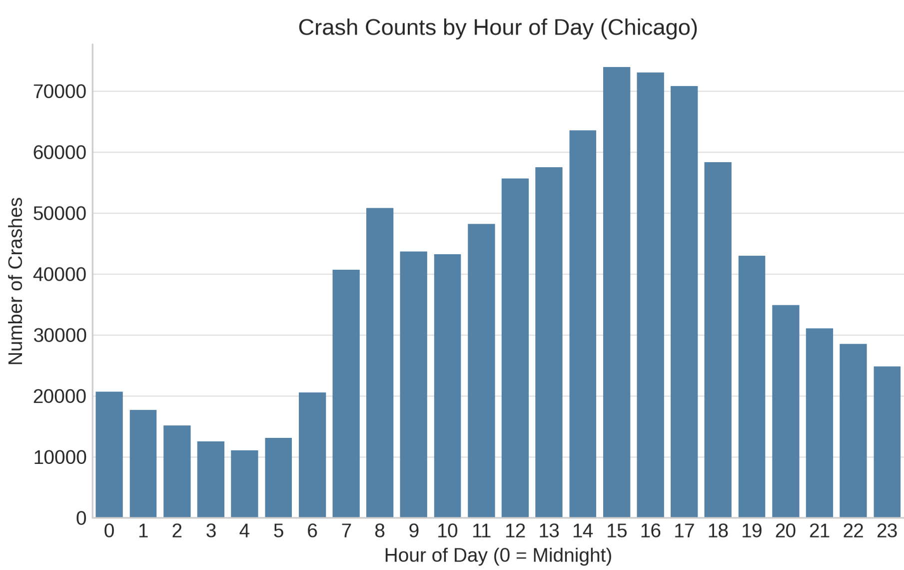

Figure 13: Crash counts by hour of the day in Chicago.

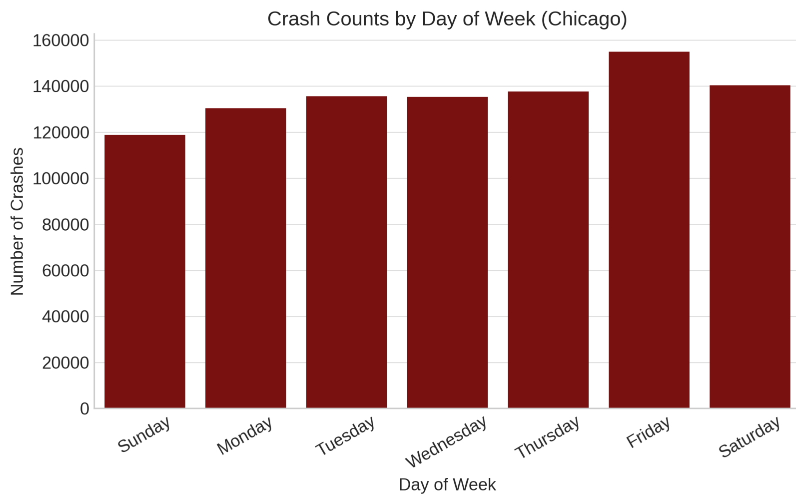

Figure 14: Crash counts by day of the week in Chicago.

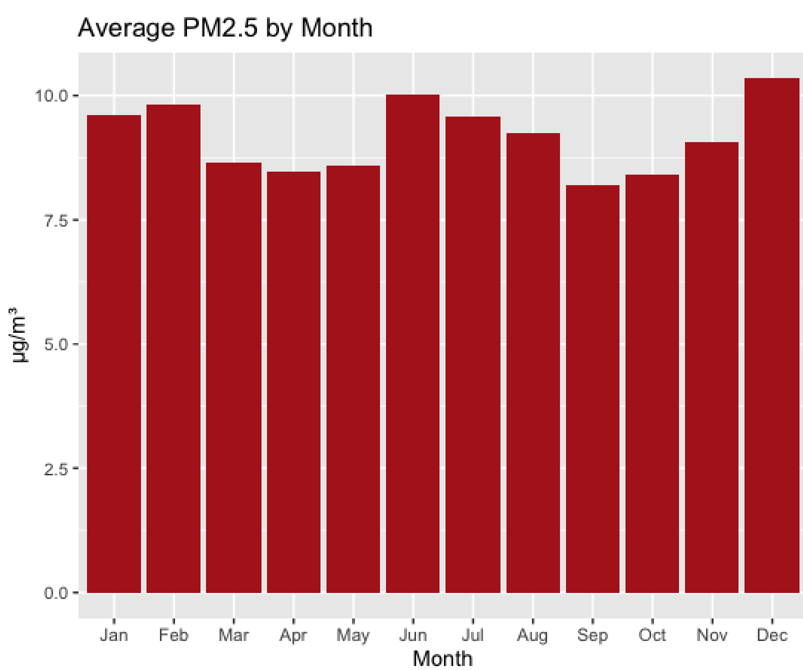

Figure 15: Average PM2.5 by Month

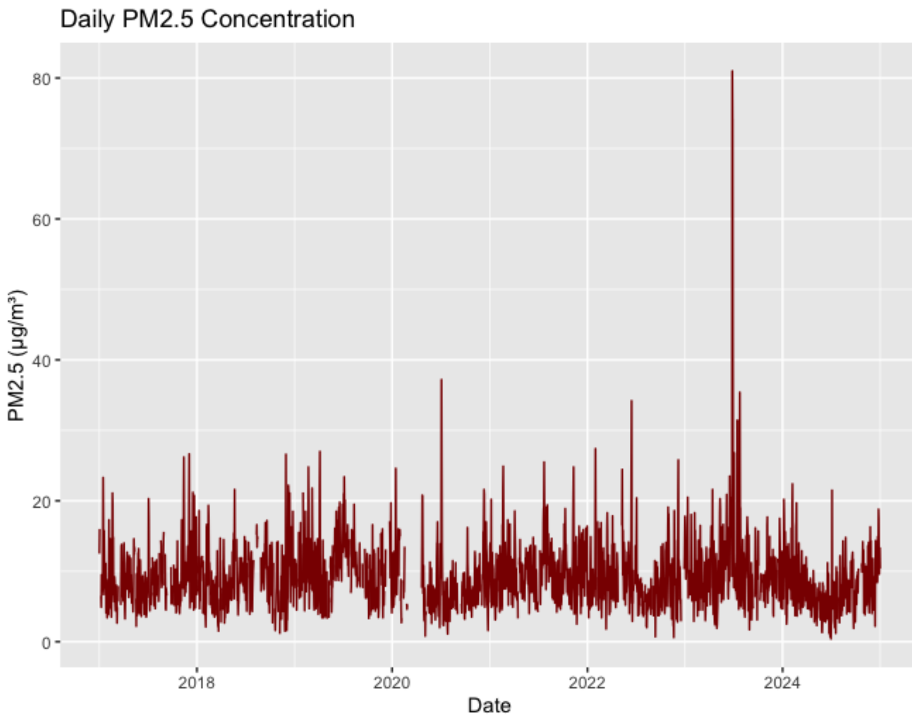

Figure 16: Daily PM2.5 Concentration in Chicago

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: US

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/m³ 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*.

Table 6: Crash Characteristics by Injury Severity

	Injury Severity Category				
	No Injury	Reported, Not Evident	Non-Incapacitating	Incapacitating	Fatal
Observations					
Count	816,068	42,652	75,364	15,680	1,024
Percent of total	85.83	4.49	7.93	1.65	0.11
Roadway Characteristics					
Avg. posted speed limit (mph)	28.2	29.6	29.6	29.8	30.0
Temporal Patterns (%)					
Rush hour (7-9am, 4-6pm)	35.7	36.3	33.6	30.7	16.2
Environmental Conditions (%)					
Darkness (lighted or unlighted)	25.6	28.1	33.1	36.4	57.7
Adverse weather	18.9	18.0	16.2	15.1	15.2
Wet or icy road surface	16.5	19.9	18.8	17.7	17.2

Notes: This table presents summary statistics for traffic crashes in Chicago from 2017 to 2024, excluding 2020-2021. The sample includes 950,788 crashes with non-missing injury severity information. Injury severity categories are mutually exclusive and ordered from least to most severe. Rush hour is defined as weekday crashes occurring between 7-9am or 4-6pm. Adverse weather includes rain, snow, fog, freezing rain, and severe weather conditions. Darkness includes both lighted and unlighted road conditions.

Table 7: Distribution of Weather and Lighting Conditions

Condition	Observations	Percent
Weather Condition		
Clear	747,397	78.4
Rain	82,247	8.6
Snow	30,715	3.2
Cloudy/Overcast	28,128	3.0
Unknown	58,880	6.2
Freezing Rain/Sleet	3,435	0.4
Fog/Smoke/Haze	1,413	0.1
Severe Weather	671	0.1
Lighting Condition		
Daylight	611,168	64.1
Darkness, lighted road	208,329	21.9
Unknown	45,786	4.8
Darkness, unlighted	44,710	4.7
Dusk	27,056	2.8
Dawn	15,837	1.7

Notes: This table shows the distribution of weather and lighting conditions across all crashes in the sample (952,886 total crashes). The majority of crashes occur in clear weather (78.4%) and daylight conditions (64.1%). Severe weather includes blowing snow, blowing sand/soil/dirt, and severe wind conditions.

Table 8: Ordered Logit: Determinants of Crash Injury Severity

	Dependent variable: Injury Severity		
	(1)	(2)	(3)
Roadway Characteristics			
Posted Speed Limit	0.046***	0.043***	0.043***
	(0.001)	(0.001)	(0.001)
Weather Conditions			
Cloudy		0.113***	0.113***
		(0.017)	(0.017)
Rain		0.029	0.030
		(0.016)	(0.016)
Snow		-0.061**	-0.061**
		(0.024)	(0.024)
Freezing Rain		0.164***	0.164***
		(0.048)	(0.048)
Fog		0.104	0.105
		(0.070)	(0.070)
Severe Weather		0.225**	0.226**
		(0.108)	(0.108)
Unknown		-0.251***	-0.251***
		(0.024)	(0.024)
Lighting Conditions			
Dawn		0.183***	0.180***
		(0.022)	(0.022)
Dusk		0.117***	0.121***
		(0.017)	(0.018)
Darkness, Lighted Road		0.322***	0.313***
		(0.007)	(0.007)
Darkness, Unlighted		0.016	0.009
		(0.015)	(0.015)
Unknown		-0.809***	-0.811***
		(0.028)	(0.028)
Road Surface			
Wet		0.121***	0.122***
		(0.014)	(0.014)
Ice/Snow		-0.325***	-0.323***
		(0.023)	(0.023)
Other		0.225***	0.225***
		(0.054)	(0.054)
Unknown		-0.421***	-0.421***
		(0.017)	(0.017)
Temporal Controls			
Rush Hour			-0.035***
			(0.006)
Observations	915,224	915,224	915,224
AIC	1,013,432	1,004,019	1,003,991

Notes: *p<0.10; **p<0.05; ***p<0.01. Dependent variable is injury severity (ordered): None, Reported Not Evident, Non-Incapacitating, Incapacitating, Fatal. Coefficients are log odds ratios from ordered logistic regression.

Table 9: Ordered Logit: Effect of PM2.5 on Crash Injury Severity

	Dependent variable: Injury Severity		
	Base	Add PM2.5	Add FE
	(1)	(2)	(3)
Air Quality			
PM2.5 (µg/m^3)		0.0005	0.003***
		(0.001)	(0.001)
Roadway Characteristics			
Posted Speed Limit	0.044***	0.044***	0.044***
	(0.001)	(0.001)	(0.001)
Weather Conditions			
Cloudy	0.096***	0.096***	0.111***
	(0.019)	(0.019)	(0.019)
Rain	0.033	0.033	-0.007
	(0.017)	(0.017)	(0.018)
Snow	-0.041	-0.040	0.002
	(0.026)	(0.026)	(0.027)
Freezing Rain	0.171***	0.171***	0.160***
	(0.054)	(0.054)	(0.054)
Lighting Conditions			
Dawn	0.178***	0.178***	0.190***
	(0.024)	(0.024)	(0.024)
Dusk	0.129***	0.129***	0.146***
	(0.019)	(0.019)	(0.019)
Darkness, Lighted Road	0.312***	0.311***	0.332***
	(0.008)	(0.008)	(0.008)
Darkness, Unlighted	0.014	0.014	0.048***
	(0.016)	(0.016)	(0.016)
Road Surface			
Wet	0.111***	0.111***	0.170***
	(0.015)	(0.015)	(0.015)
Ice/Snow	-0.337***	-0.337***	-0.197***
	(0.026)	(0.026)	(0.026)
Temporal Controls			
Rush Hour	-0.033***	-0.033***	-0.021***
	(0.007)	(0.007)	(0.007)
Year FE	No	No	Yes
Month FE	No	No	Yes
Observations	747,431	747,431	747,431
AIC	838,570	838,572	836,318

Notes: *p<0.10; **p<0.05; ***p<0.01. Standard errors in parentheses. Dependent variable is injury severity (ordered): None, Reported Not Evident, Non-Incapacitating, Incapacitating, Fatal. Coefficients are log odds ratios from ordered logistic regression. Column (1) excludes PM2.5; (2) adds PM2.5; (3) adds year and month FE. This examines reduced-form relationship; we do not instrument in individual-level setting due to complexity of IV with ordered models and because main causal identification comes from IV on aggregate crash counts.

Table 10: OLS: Effect of $PM_{2.5}$ on Daily Crashes in Chicago

	Dependent variable:		
	Total Crashes	Fatal Crashes	Non-Fatal Crashes
	(1)	(2)	(3)
$PM_{2.5}$ (μg/m^3)	−0.080	−0.001	−0.079
	(0.263)	(0.003)	(0.262)
Rain Intensity	10.055***	0.010	9.866***
	(2.525)	(0.027)	(2.519)
Wind Speed	−2.163***	−0.020**	−2.162***
	(0.741)	(0.008)	(0.739)
Day-of-Week FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Mean of Dep. Var.	297.0	0.305	296.0
Observations	1,924	1,924	1,924

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. Weather controls include rain intensity and wind speed.

Table 11: IV: Effect of $PM_{2.5}$ on Daily Crashes in Chicago (4 Wind Direction Bins)

	Dependent variable:		
	Total Crashes	Fatal Crashes	Non-Fatal Crashes
	(1)	(2)	(3)
$PM_{2.5}$ (μg/m^3)	2.314**	0.028**	2.300**
	(1.134)	(0.012)	(1.131)
Rain Intensity	10.600***	0.016	10.407***
	(2.591)	(0.028)	(2.585)
Wind Speed	−1.061	−0.007	−1.066
	(0.911)	(0.010)	(0.909)
Day-of-Week FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Number of Instruments	3	3	3
Mean of Dep. Var.	297.0	0.305	296.0
Percentage Effect	0.78%	9.05%	0.78%
First-stage F-stat	37.8	37.8	37.8
Observations	1,924	1,924	1,924

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. Instruments: Three wind direction bin indicators (90° bins: N-NE, E-SE, S-SW; reference: W-NW). Weather controls include rain intensity and wind speed. First-stage F-statistic exceeds Stock-Yogo critical value of 22.3 for 10% maximal IV size with three instruments.

Table 12: IV: Effect of $PM_{2.5}$ on Daily Crashes in Chicago (8 Wind Direction Bins)

	Dependent variable:		
	Total Crashes (1)	Fatal Crashes (2)	Non-Fatal Crashes (3)
$PM_{2.5}$ (μg/m^3)	1.600*	0.020*	1.593*
	(1.079)	(0.012)	(1.076)
Rain Intensity	10.437***	0.015	10.246***
	(2.563)	(0.028)	(2.557)
Wind Speed	−1.389	−0.010	−1.392
	(0.890)	(0.010)	(0.888)
Day-of-Week FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
Weather Controls	Yes	Yes	Yes
Number of Instruments	7	7	7
Mean of Dep. Var.	297.0	0.305	296.0
Percentage Effect	0.54%	6.46%	0.54%
First-stage F-stat	17.6	17.6	17.6
Observations	1,924	1,924	1,924

Notes: *p<0.1; **p<0.05; ***p<0.01. Standard errors in parentheses. Instruments: Seven wind direction bin indicators (45° bins; reference: NW 315°-360°). Weather controls include rain intensity and wind speed. Results presented for robustness; main specifications use 4-bin instrument.

Table 13: Descriptive Statistics: Chicago

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
Total Crashes	2,922	291.77	63.95	85.00	255.00	298.50	333.00	583.00
Fatal Crashes	2,922	0.33	0.60	0.00	0.00	0.00	1.00	6.00
Non-Fatal Crashes	2,922	290.79	63.82	84.00	254.00	297.00	331.00	582.00
Average Temperature (°C)	2,576	12.63	10.16	-25.87	4.44	13.39	21.73	31.71
Average Rain Intensity (mm/hr)	2,576	0.15	0.49	0.00	0.00	0.00	0.04	6.22
Average Total Rain (mm)	2,576	123.77	147.97	0.00	20.38	57.99	177.51	912.20
Average Wind Direction (degrees)	2,576	177.26	70.13	6.00	121.79	177.06	233.46	338.46
Average Wind Speed (m/s)	2,576	2.72	1.62	0.58	1.79	2.41	3.28	44.83
Maximum Wind Speed (m/s)	2,576	10.33	35.03	1.70	6.50	8.50	11.00	-
Average PM2.5 (µg/m^3)	2,650	9.18	4.66	0.40	6.10	8.50	11.30	81.00
Average AQI	2,650	44.95	14.85	2.00	34.00	47.00	55.00	169.00

Notes: This table presents descriptive statistics for daily observations of traffic crashes, weather conditions, and air pollution levels in Chicago from 2017 to 2025.

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