Tohoku University Research Center for Policy Design Discussion Paper

TUPD-2026-018

Pollution and Traffics Accidents in Brazil

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Oct 2026

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Pollution and Traffics Accidents in Brazil

Christian Rodriguez Rivas1 Akira Hibiki [2]

Abstract

Road traffic accidents are a leading cause of preventable death, but little is known about how environmental conditions shape the driver behavior behind them. This paper estimates the effect of short-term exposure to fine particulate matter ($PM_{2.5}$) on traffic accidents in Brazil and through which behavioral channels it operates. We use daily Highway Patrol records for 2017–2019 from São Paulo, Rio de Janeiro, Espírito Santo and Minas Gerais. Each accident is classified by primary cause: aggressive driving, driver error, or substance-related and other causes. To address the endogeneity of pollution, we instrument $PM_{2.5}$ with thermal inversions in a two-stage least squares framework. Pollution increases the number of accidents. The effects are driven by aggressive driving and driver error, while substance-related and other causes, used as a placebo, show no significant response. The effect is concentrated on the day of exposure, with no significant leads or lags. These results suggest that $PM_{2.5}$ affects road safety through behavioral and cognitive channels, so air quality policy may bring road safety benefits as well as health gains.

Keywords: Traffic accidents, $PM_{2.5}$, highways

JEL Classification: Q53, R41, I18, C26.

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Introduction

Road traffic accidents are one of the leading causes of preventable death and disability worldwide; however, a significant share of their determinants remain still unknown. Individual behavior such as speeding, alcohol consumption, and inattention has long been recognized as the dominant driver of accident risk, less attention has been paid to how environmental conditions shape those behaviors in the first place. This chapter examines ambient air pollution and its effects on traffic accidents.

The central question is whether short-term exposure to particulate matter known as $PM_{2.5}$ can increase traffic accidents, and if so, through which behavioral channels. Our hypothesis is that air pollution triggers neuroinflammatory responses and oxidative stress in regions of the brain governing attention, emotional regulation, and impulse control. If these biological effects are large enough to meaningfully impair driving performance, they should show up in accident data, particularly in accidents attributed to aggressive behavior and cognitive errors rather than substance intoxication or mechanical failure.

To test this, we use daily traffic accident records from the Brazilian Highway Patrol across four major states, São Paulo, Rio de Janeiro, Espírito Santo, and Mato Grosso which covers nearly 200,000 route-region-day observations. A key feature of the data is that each accident is classified by its primary cause, which allows us to decompose effects across three behavioral categories: aggressive driving, driver error, and substance-related or other causes. This fault-type decomposition is the main methodological contribution of the chapter relative to the existing literature, which has established that pollution raises accident risk but has not been able to identify the specific behavioral mechanism.

Estimating the causal effect of pollution is complicated by the fact that human activity generates both pollution and the conditions that give rise to accidents. To address this endogeneity, we exploit thermal inversions which are meteorological events that trap ground-level pollutants by preventing normal vertical air circulation. This environmental phenomenon is generally used as an instrument for daily $PM_{2.5}$ concentrations in literature. Because inversions are driven by large-scale atmospheric

dynamics, they generate plausibly exogenous variation in pollution that is unrelated to local traffic conditions or economic activity.

The results show that a one standard deviation increase $PM_{2.5}$ concentrations (around 10 $\mu g/m^3$) raises total daily accidents by approximately 3 percent. Disaggregating by fault type, the effects are concentrated in a larger part due to aggressive driving and followed by driver error, while substance-related and other causes show no significant response which is consistent with pollution operating through behavioral and cognitive channels rather than indiscriminately raising all accident types. These findings hold across vehicle types, age groups, and both genders, and are robust to alternative inversion definitions, sample restrictions, and functional form choices.

Background

1.The Global and Brazilian Burden of Road Traffic Injuries

Road accidents represent one of the leading causes of death and injuries in our time. According to the World Health Organization (2023), around 1.19 million people were involved in traffic road crashes in 2021, making it the leading cause of death among the age groups of 5 to 29 years and the twelfth leading cause of death across all age groups. In addition, the burden falls disproportionately on the working-age population, with two-thirds of victims aged between 18 and 59, generating substantial economic and social costs beyond the immediate human life lost. When accounting for the means of transport, motorcyclists and powered two-wheeler riders account for 30 percent of all fatalities, followed by occupants of four-wheeled vehicles at 25 percent and pedestrians at 21 percent. This distribution reflects the vulnerability of unprotected road users in mixed-traffic environments.

The geographic concentration of traffic accidents is also important to consider. Almost nine in ten road traffic deaths occur in low- middle-income countries, and the Region of the Americas recorded no reduction in road traffic deaths between 2010 and 2021, in sharp contrast to the 36 percent decline achieved in Europe over the same period (WHO, 2023). The situation is particularly troubling if we also include that the global motor vehicle fleet more than doubled during this period, suggesting that the

infrastructure investments and behavioral interventions that have driven progress in high-income countries have not been replicated at scale in developing countries. Despite decades of awareness of the principal behavioral risk factors such as speeding, impaired driving, and failure to use protective equipment, only seven countries worldwide have achieved best-practice legislation across all five major risk factors identified by the WHO, pointing to a persistent gap between knowledge and political will.

Brazil exemplifies this challenge. As a large middle-income country experiencing rapid motorization, it has seen road traffic injuries emerge as a leading cause of preventable death and disability. Morais Neto et al. (2016) document substantial regional heterogeneity in road traffic injury rates across Brazil's macroregions. Their analysis identifies being male, young, and engaging in binge drinking as the strongest individual-level predictors of injury, with motorcyclists facing particularly elevated risk which is consistent with the national vehicle mix and the rapid diffusion of motorcycle transport in low-income regions. De Andrade et al. (2014) complement this picture with a spatial analysis of fatalities along a major federal highway in Paraná, identifying infrastructure characteristics such as double-lane sections, limited lighting, and reduced auxiliary lanes as key environmental determinants of crash hotspots.

Beyond individual behavior and infrastructure, a growing body of evidence points to environmental stressors as a component of road safety that haven’t been determined yet in detail. De Carvalho et al. (2024), drawing on data from Brazilian federal highways, show that human factors including inattention, speeding, and alcohol consumption remain the dominant contributors to accident causation even after accounting for physical road conditions. However, this paper underscores the importance of understanding how environmental conditions may modulate driver behavior rather than acting through mechanical or infrastructural channels alone. The present paper builds on this insight by examining one specific environmental channel, ambient air pollution, as a causal of accident risk operating through its effects on driver cognition and behavior.

2. Behavioral Causes of Traffic Accidents

2.1 Taxonomy of Accident Causes

Accidents are not the result of a single behavioral or external factor; rather, they emerge from distinct mechanisms operating through different psychological and physiological pathways. Understanding these mechanisms is important because environmental stressors may affect some forms of risky behavior while leaving others unchanged. This study classifies accident causes into three broad categories: aggressive driving, cognitive or attentional errors, and substance-related or other causes.

This classification is consistent with evidence that accidents cause cluster into empirically distinct behavioral dimensions. Using a large sample of police-reported crashes, Rolison et al. (2018) show that risky and aggressive behaviors, cognitive failures, and substance impairment represent separate dimensions of accident causation rather than manifestations of a single underlying propensity for risk. Aggressive behaviors are typically associated with deliberate violations of traffic rules, such as incompatible speed, unsafe overtaking, and tailgating. Cognitive errors arise from failures of attention, information processing, or decision-making during driving. Substance-related crashes, by contrast, are linked to alcohol or drug impairment and are generally identified as a distinct category by law enforcement agencies.

The distinction is particularly relevant for the empirical strategy of this paper. If air pollution affects driving behavior through psychological stress, emotional arousal, or cognitive impairment, its effects should be concentrated in aggressive and error-related accidents. Substance-related causes, which are primarily determined by prior alcohol or drug consumption decisions, should be considerably less sensitive to short-run fluctuations in ambient pollution and thus, making them a natural placebo outcome in the empirical analysis.

2.2 Aggressive Driving

Aggressive driving constitutes one of the most important behavioral determinants of traffic accidents. Unlike cognitive errors, which arise from failures in information processing, aggressive driving involves intentional violations of traffic norms and

elevated risk-taking. Common manifestations include incompatible speed for the maneuver, unsafe lane changes, following too closely, and dangerous overtaking maneuvers.

Experimental evidence demonstrates that emotional states directly influence driving performance. Zhang et al. (2016) show that drivers exposed to anger-inducing conditions drive at higher speeds, maintain shorter headways, accept smaller gaps in traffic, and exhibit a narrower visual scanning pattern than drivers in neutral emotional states. These behavioral changes increase accident risk by reducing reaction time and limiting the capacity to process information from the surrounding environment. Importantly, the study finds that driving experience does not fully protect individuals from these effects, suggesting that emotional arousal can impair drivers across different demographic groups.

Aggressive driving has also been shown to represent a stable and measurable behavioral construct. Jovanović et al. (2010) find that aggressive driving is mediated by anger and related personality traits rather than by cognitive limitations. Drivers with higher levels of driving anger are more likely to engage in risky maneuvers, commit traffic violations, and become involved in crashes. This evidence supports treating aggressive driving as a distinct behavioral pathway through which external stressors may influence accident outcomes.

Gender differences further reinforce this distinction. González-Iglesias et al. (2012) document that male drivers are involved in more accidents, receive more traffic citations, and report higher rates of risky driving behaviors than female drivers, even after controlling for driving exposure. While both men and women experience driving anger, men are more likely to express it through aggressive actions behind the wheel. These findings provide a behavioral rationale for examining heterogeneity in pollution effects across gender groups in the empirical analysis.

Taken together, the literature suggests that aggressive driving is strongly influenced by emotional and physiological states. If air pollution generates psychological stress or emotional irritation, as the evidence reviewed in the following section suggests, it may

increase the likelihood of aggressive driving behaviors and consequently elevate the incidence of accidents attributable to this category.

2.3 Driver Error

A second major source of traffic accidents is attributed to cognitive failures. Unlike aggressive driving, these accidents occur when drivers experience reduced attention, impaired information processing, or excessive mental workload that compromises safe vehicle operation.

Research in transportation demonstrates that driving performance is highly sensitive to cognitive demands. Cantin et al. (2009) show that mental workload increases substantially with driving complexity and that higher workload is associated with slower reaction times and greater likelihood of driving errors. Their simulator experiments indicate that complex driving situations, such as intersections and overtaking maneuvers, impose significant cognitive burdens on drivers, particularly older individuals. As mental workload rises, drivers become less capable of processing information rapidly and responding appropriately to unexpected events.

Even minor distractions can produce meaningful deterioration in performance. Stothart et al. (2015) find that mobile phone notifications impair attention and increase error rates even when participants do not actively interact with their phones. The authors argue that notifications trigger task-irrelevant thoughts and mind wandering, diverting cognitive resources away from the primary task. The magnitude of the resulting performance decline is comparable to that observed in studies of active phone use during driving. These findings suggest that accident risk can increase substantially even in the absence of deliberate risk-taking behavior, through the degradation of attentional resources alone.

Environmental stressors on professional drivers provide additional context. Useche et al. (2018) show that work-related stress is significantly associated with traffic accidents and traffic fines among professional drivers, even after controlling physical health outcomes and demographic characteristics. This evidence supports the view that psychological and environmental stressors impair driving performance through cognitive and emotional channels rather than through purely physiological ones.

Consequently, if air pollution affects neurological functioning, concentration, or attentional capacity, as the biological evidence reviewed below suggests, it should be reflected in a higher frequency of accidents classified as driver errors.

2.4 Substance-related and other causes

Substance-related accidents differ fundamentally from both aggressive driving and cognitive errors because their immediate cause is intoxication rather than temporary changes in emotional state or attentional capacity. Alcohol and drug impairment directly affect reaction time, judgment, coordination, and risk perception through well-established pathways.

The distinction is important for identifying the mechanisms through which air pollution may affect road safety. Whereas aggressive driving and cognitive errors can plausibly respond to short-term fluctuations in environmental stress, mood, or attention, substance-related accidents depend primarily on prior consumption decisions that are unlikely to be affected by daily changes in ambient pollution concentrations. For this reason, substance-related accidents, along with mechanical failures, and road infrastructure conditions, serve as a falsification outcome in empirical analysis. Finding significant pollution effects on aggressive and error-related accidents but not on this residual category would strengthen the interpretation that pollution operates through behavioral and cognitive channels rather than through a generalized elevation of all accident types.

3. Air Pollution, Neurological Function, and Cognitive Impairment

The health consequences of air pollution extend far more than just the respiratory system. A growing literature documents that exposure to traffic-related pollutants, especially particularly particulate matter, triggers neuroinflammatory responses and oxidative stress in regions of the brain governing emotional regulation and cognitive function. Costa et al. (2015) show that even short-term exposures produce measurable changes including microglial activation and oxidative damage, particularly in the hippocampus. These effects are consistently more pronounced in male subjects due to lower baseline antioxidant capacity.

At the population level, the cognitive consequences of pollution exposure are documented across the full life course. A systematic review of 31 studies by Clifford et al. (2016) finds coherent evidence that exposure to traffic-related pollutants impairs cognitive function from childhood through older adulthood, including neurodevelopmental delays in children and accelerated cognitive decline in elderly populations. The review identifies oxidative stress, neuroinflammation, and blood-brain barrier disruption as the primary biological pathways, the same mechanisms that impair the attentional capacity, reaction time, and emotional regulation that are directly relevant to safe driving.

Importantly, effects are documented not only at high chronic exposure levels but also following acute exposures. This is directly relevant to the identification strategy of this paper, which exploits day-to-day variation in pollution concentrations generated by thermal inversions to estimate short-run causal effects on driver behavior. The biological plausibility of acute effects is further supported by Clifford et al. (2016) observation that effects are particularly pronounced at both ends of the age distribution, among the young and the elderly, consistent with the age heterogeneity documented in the empirical analysis.

4. Air Pollution and Aggressive Behavior: Evidence from Crime

A complementary strand of evidence establishes that air pollution affects aggressive behavior in non-driving contexts, providing additional support for the behavioral mechanism proposed in this paper.

Burkhardt et al. (2019) find that a 10 percent increase in $PM_{2.5}$ concentration leads to a measurable increase in violent crimes per county per day in the United States, driven entirely by assaults with no corresponding effect on property crimes. This pattern, aggressive behavior affected, economically motivated behavior unaffected, provides a close behavioral analogue to the finding in this paper that pollution increases aggressive driving and driver error accidents while leaving substance-related and mechanical causes unchanged. The authors attribute this effect to systemic inflammation impairing cognitive and emotional regulation, the same biological channel identified in the literature.

Herrnstadt et al. (2021) provide causal evidence using wind direction as a source of exogenous pollution variation in Chicago, finding that downwind neighborhoods experience higher rates of violent crime but no increase in property crime. The contemporaneous nature of this effect, absent in leads or lags, is consistent with the dynamic specification in this paper, which shows that pollution effects on accidents are concentrated on the day of exposure. Bondy et al. (2019) reach similar conclusions in London using atmospheric thermal inversions as an instrument and find effects at pollution levels well below current regulatory and recommended health related thresholds, suggesting that behavioral responses to air pollution are not confined to extreme pollution episodes as it is found in this paper.

Together, this crime literature establishes that the behavioral pathway from pollution to aggression is not specific to the driving context. The present paper extends this evidence by examining an economically important behavioral domain of road safety and by providing a richer decomposition of behavioral mechanisms using fault-type data unavailable in crime records.

5. Air Pollution and Road Traffic Accidents

Closest to this paper is a small but growing literature establishing causal links between air pollution and traffic accident risk. Sager (2019) provides the first such evidence, documenting a 0.3–0.6 percent increase in vehicles involved in accidents per microgram per cubic meter of $PM_{2.5}$ in the United Kingdom, using thermal inversions as an instrument. That study demonstrates that the effect operates through cognitive or behavioral channels rather than through changes in traffic volume, but it cannot distinguish whether the mechanism is cognitive impairment, increased aggression, or some combination of the two. The present paper addresses this gap directly by decomposing accidents by behavioral cause, providing the first causal evidence on the specific pathways through which air pollution affects driving behavior.

Braun and Villas-Boas (2023) find that $PM_{2.5}$ increases fatal traffic accidents in California by approximately 1.3 percent per microgram per cubic meter using a similar instrumental variables approach, with effects concentrated in lower-income counties — a pattern consistent with differential pollution exposure and limited mitigation

capacity. They explicitly call for future research investigating heterogeneity in accident types and driver characteristics, a gap this paper addresses through the fault-type decomposition.

An informative contrast comes from Shr et al. (2023) who find that elevated $PM_{2.5}$ reduces accidents caused by driver violations in Taiwan. The authors attribute this to visual risk aversion: when pollution is sufficiently high to be visible, drivers slow down and exercise greater caution. Critically, this effect operates only during daylight hours when drivers can perceive the visual effects of air quality is and is absent for accidents caused by cognitive errors. This finding is consistent with a nonlinear dose-response where visual salience of pollution generates compensatory behavior at high concentrations. In the Brazilian setting analyzed here, mean $PM_{2.5}$ concentrations are moderate (11.7 $\mu g/m^3$) and generally below the threshold of visual perceptibility, implying that the cognitive impairment channel dominates over visual risk aversion — yielding effects in the opposite direction to those documented in Taiwan.

Complementary evidence is provided by Danagoulian and Deza (2024) who show that high pollen days increase fatal accidents by approximately 5.8 percent, with effects driven by cognitive impairment rather than mechanical factors or avoidance behavior. Since people do not systematically reduce driving on high-pollen days, this finding parallels the Brazilian context where drivers cannot directly observe $PM_{2.5}$ concentrations and therefore cannot adjust their behavior in anticipation of elevated pollution exposure.

6. Thermal Inversions as an Identification Strategy

A central challenge in estimating the causal effect of air pollution on traffic accidents is the endogeneity of pollution. Human activity generates both pollution and the conditions that give rise to accidents: surges in road traffic simultaneously increase emissions and accident exposure; industrial activity patterns vary seasonally in ways that correlate with human mobility; and burning events generate both pollution and reduced road visibility. These confounders make it impossible to recover unbiased causal estimates from observational variation in pollution alone.

This paper addresses this challenge by exploiting thermal inversions as a source of exogenous variation in $PM_{2.5}$ concentrations. A thermal inversion occurs when a warmer air mass sits above a cooler surface layer, suppressing the vertical mixing that normally disperses pollutants. Under inversion conditions, emissions from traffic, industry, and other ground-level sources become trapped near the surface, causing localized increases in ambient pollution concentrations. Because thermal inversions are driven by atmospheric dynamics — specifically by large-scale meteorological patterns governing temperature— they are plausibly orthogonal to the local economic and behavioral factors that confound the pollution-accident relationship making it a good instrument for air pollution since it does not affect traffic accidents through any other channel.

The validity of this identification strategy rests on two conditions. First, thermal inversions must be strongly predictive of pollution concentrations — a condition confirmed by the first-stage results, which show a Kleibergen-Paap F-statistic well above conventional thresholds. Second, inversions must affect accident risk only through their effect on pollution, and not through direct effects on driving conditions. This exclusion restriction is supported by the nature of the phenomenon: thermal inversions do not alter road surface conditions, visibility, or traffic volumes in ways that independently affect accident risk. The dynamic specification, which shows that accident effects are concentrated on the contemporaneous day of inversion exposure with no significant leads or lags, further supports this interpretation — ruling out the possibility that inversions proxy for pre-existing behavioral trends.

Data

Traffic Accidents

We use traffic accident records from the Highway Patrol of Brazil, covering the four largest federative units by population: São Paulo, Rio de Janeiro, Espírito Santo, and Mato Grosso from 2017 to 2019. Together, these states account for 40 percent of Brazil's total population and concentrate the country's main industrial activity, making them a representative and sufficiently populated sample for the study.

Our unit of observation is the daily number of accidents per immediate region per route. Brazil uses a geographic division called Immediate and Intermediate Regions — areas defined independently of administrative boundaries; each organized around a common economic hub and shared labor market. This means people routinely commute within these regions daily, which helps reduce measurement error in pollution exposure. The average immediate region covers 6,380 square kilometers.

Beyond accident counts, the data include rich details on each incident, including the cause of the accident which is our main proxy for driver behavior. We classify accidents into three mutually exclusive categories based on their primary cause.

First, aggressive behavior covers accidents resulting from deliberate but impulsive decisions, such as incompatible speed, improper overtaking, failure to maintain a safe distance, disobedience of traffic rules, and external aggression toward other road users. Second, human error captures cognitive and physiological failures that impair safe vehicle operation, including inattention, delayed reaction. These two categories are the primary outcomes of interest, as both have been linked in the literature to neurological and physiological responses to air pollution exposure. Third, substance-related and other causes aggregate all remaining accidents which are unrelated to behavioral or cognitive responses to environmental stimuli such as alcohol and psychoactive substance consumption, mechanical defects, road infrastructure failures, restricted visibility, natural phenomena, and pedestrian-related factors. This category serves as the falsification test: there is no plausible biological or behavioral mechanism through which short-term variation in $PM_{2.5}$, instrumented by thermal inversions, would systematically affect accidents driven by intoxication, mechanical failure, or road conditions.

Since the outcome data includes zero values for some observations, we apply two transformations: a hyperbolic sine transformation and a log transformation with an added constant of one for the cases with zero accidents in the observations. Methods commonly employed in previous literature.

Weather Data

Weather variables come from the automatic stations of the National Institute of Meteorology (INMET). We use 150 stations within the study area, with hourly observations aggregated to the daily level. Values are then interpolated to each immediate region centroid using the four closest stations, weighted by inverse squared distance elevated to the second power to account for a higher weight for the closest stations to the region centroids. The weather controls included are temperature, precipitation, atmospheric pressure, humidity, wind direction, and wind speed.

Thermal Inversions

Air pollution is not exogenous in our context, it is influenced by industrial activity, agricultural production, and traffic congestion. For instance, a surge in vehicles on the highway raises pollution and may simultaneously increase accident risk through greater traffic exposure or reduce it through congestion-induced slowdowns. To address this endogeneity, we instrument $PM_{2.5}$ with thermal inversions.

A thermal inversion occurs when a warmer air mass sits above a cooler surface layer, preventing normal vertical air circulation. Ground-level pollutants become trapped in the cooler layer and cannot disperse. Inversions satisfy the conditions for a valid instrument: they directly affect pollution concentrations but have no independent effect on traffic accident rates.

We construct the inversion indicator using the ERA5 reanalysis dataset, comparing hourly temperature measurements at two pressure levels — 1000 hPa (approximately sea level) and 975 hPa (approximately 350 meters above sea level) on a 0.25° × 0.25° grid (roughly 25 km × 25 km). We use measurements taken at 3 AM and interpolate the four closest grid points to each region centroid using inverse squared distance weighting. A dummy is assigned to equal one when the upper layer is warmer than the lower layer and 0 for the opposite case.

Pollution

Our main pollution measure is ground-level $PM_{2.5}$, drawn from the EAC4 dataset (ECMWF Atmospheric Composition Reanalysis 4) provided by Copernicus. The dataset

has a horizontal resolution of 0.75° × 0.75° and observations every three hours. We aggregate to the daily average for each grid cell and interpolate the four closest grid points to each region centroid using inverse squared distance weighting. Table 1 presents summary statistics for all variables used in the analysis.

Methodology

To account for the effects of air pollution on traffic accidents, we employed the following model to measure the impact of pm25 on traffic accidents by cause in equation 1.

$$Y_{krit} = \beta_1 PM2.5_{rit} + \theta X_{rit} + \pi_i + \varpi_{rt} + \tau_t + \varepsilon_{rit} \quad (1)$$

Were Y_{krit} accounts for the transformation of the number of accidents by source on route *r* in region *i* in date *t*. β_1 is our coefficient of main interest since it accounts for the effects of air pollution on the traffic accidents number. X_{rit} is our set of weather variables including temperature, humidity, precipitation, wind speed, atmospheric pressure and wind direction. π_i are our region fixed effects to account for time invariant characteristics of the region, ϖ_{rt} are our route by day of the week fixed effects to account for the traffic volume in each day by route and τ_t are our month by year fixed effects to account for any time variant pattern that might affect the traffic level such as holidays season or industry seasonality.

Table 1. Summary Statistics

Panel A: Accidents Outcomes					
	N	Mean	SD	Min	Max
Accidents	196,005	0.884	3.092	0	244
Aggressive	196,005	0.305	1.54	0	144
Driving Error	196,005	0.371	1.467	0	112
Substance or other cause	196,005	0.208	1.114	0	112
Panel B: Vehicles/Demographics					
	N	Mean	SD	Min	Max
Car	196,005	0.486	1.984	0	160
Bicycle	196,005	0.185	0.836	0	33
Large Vehicle	196,005	0.209	1.161	0	140
Age 0-17	196,005	0.002	0.083	0	16
Age 18-24	196,005	0.089	0.554	0	40
Age 25-34	196,005	0.228	1.054	0	80
Age 35-44	196,005	0.228	1.076	0	96

Age 45-54	196,005	0.151	0.836	0	140
Age 55-64	196,005	0.09	0.558	0	45
Age 65+	196,005	0.039	0.338	0	36
Female	196,005	0.082	0.523	0	41
Male	196,005	0.756	2.717	0	225
Panel C: Environmental Variables					
	N	Mean	SD	Min	Max
Thermal Inversion Dummy	196,005	0.622	0.485	0	1
Precipitation (mm)	196,005	0.148	0.363	0	7.418
Atmospheric Pressure (hPa)	196,005	946.11	38.572	818.149	1028.9
Temperature (°C)	196,005	21.899	3.448	5.244	34.572
Humidity (%)	196,005	72.419	11.762	17.494	99.822
Wind Speed (m/s)	195,958	1.782	0.801	0	6.971
Panel D: Pollution					
	N	Mean	SD	Min	Max
$PM_{2.5}$ (μg/m³)	196,005	11.697	9.606	0.512	380.84

As we discussed before, the effect of PM25 cannot be treated as exogenous since there are many human induced activities that can affect both the pollution level and traffic level. There are two possible outcomes of bias for our coefficient of interest, first the number of cars is higher and this results in higher accidents and also in a large amount of pollution emitted by cars, however our specification will only capture the effect of the number of cars since it is an unobservable factor captured in the error term. On the other hand, and opposite scenario where the level of pollution is higher due to the number of cars but since there is congestion the cars do not move as fast as they normally do, resulting in a decrease in the number of accidents compared to the normal conditions resulting in a downward bias. To account for the bias of both scenarios, we employed the thermal inversion as an instrument for the pollution level using a two stage least square regression as follows in equation 2.

$$PM2.5_{krit} = \alpha_1 Thermal_Inversion_{rit} + \theta X_{rit} + \pi_i + \varpi_{rt} + \tau_t + \varepsilon_{rit}$$
$$Y_{krit} = \beta_1 PM2.5_{rit} + \theta X_{rit} + \pi_i + \varpi_{rt} + \tau_t + \varepsilon_{rit} \quad (2)$$

Where we first regress the thermal inversion on the $PM_{2.5}$ to capture the effects of the inversion on the level of $PM_{2.5}$. This method will lead to a more consistent coefficient value since we account for the effects of the inversion to capture the real value of air

pollution without the interference of the unobservable factors that are not addressed in the specification.

Results

We present the baseline set of results, examining how $PM_{2.5}$ concentration relates to traffic accidents overall and different classification by cause of the incident mentioned in the previous part. The dependent variables consist of the total accidents and our three fault-based subcategories; aggressive driving, driver error, and substance or other related causes.

Table 2 reports OLS estimates. The coefficient on $PM_{2.5}$ for total accidents is positive across both functional form specifications but does not reach levels of statistical significance, suggesting that the coefficient for air pollution and accidents might suffer from endogeneity since $PM_{2.5}$ can be affected by human activity. However, disaggregating by fault type reveals a more nuanced picture. $PM_{2.5}$ enters positively and with marginal statistical significance for aggressive driving outcomes in both the hyperbolic sine transformation and log specifications in columns 3 and 6, indicating that even in OLS, there is some evidence that higher pollution is associated with a greater incidence of accidents attributable to aggressive behavior behind the wheel. The driver error and substance/other categories show no significant $PM_{2.5}$ effects in OLS, pointing toward aggressive behavior as the primary behavioral channel through which pollution may operate.

Table 2. OLS Results

Panel A. Estimates Results Using Hyperbolic Sine Transformation				
	(1)	(2)	(3)	(4)
	Accidents	Aggressive	Error	Sub/Other
$PM_{2.5}$	0.000262	0.000238*	-0.000147	0.000134
	(0.000219)	*(0.000132)*	*(0.000179)*	*(0.000114)*
N	195,958	195,958	195,958	195,958
R^2	0.247	0.124	0.178	0.114
Panel B. Estimates Results Using Log Transformation				
	(5)	(6)	(7)	(8)
	Accidents	Aggressive	Error	Sub/Other
$PM_{2.5}$	0.000203	0.000187*	-0.000116	0.000105
	(0.000175)	*(0.000102)*	*(0.000141)*	*(0.0000889)*

N	195,958	195,958	195,958	195,958
R^2	0.247	0.124	0.178	0.113

Note: All regressions outcomes are transformed by the hyperbolic sine transformation or the log transformation of log(Y+1). All equations use controls for weather variables such as temperature, humidity, precipitation, wind speed, atmospheric pressure and wind direction. All equations employ region, route-day-week and month-year fixed effects. Standard errors are clustered two-way clustered at the region-date level. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Instrumented variable results

Table 3 presents the results of the first stage regression where we employ a dummy for thermal inversions as the instrument for $PM_{2.5}$ pollution level. We can see that the relationship is positive and statistically significant with a marginal increase of 2.5 micrograms per cubic meter when we have presence of thermal inversions. In addition, we present the f value of the first stage regression with a significant score of 18.00 in the following tables we also present the kp f tests for weak instrument for the first stage regression.

Table 3. Frist Stage Results

	(1)
	$PM_{2.5}$
Thermal Inversion	2.543***
	(0.543)
Temperature	0.895***
	(0.118)
Humidity	0.0536*
	(0.0277)
Precipitation	1.336***
	(0.261)
Wind Speed	-1.494***
	(0.424)
Pressure	-0.0924***
	(0.0151)
N	195958

R-sq	0.508
F	18.00

Note: The equation employes region, route-day-week and month-year fixed effects. Standard errors are clustered two-way clustered at the region-date level. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 4 presents the coefficients of the second stage regression instrumenting for $PM_{2.5}$ with thermal inversions as source that isolates plausibly exogenous variation in pollution exposure. This instrument is quite robust and well used in literature since it avoids endogeneity that arises with pollution and other confounded factors such as level of traffic and the congestion.

The shift from OLS to an instrumental variable model produces a striking change in the $PM_{2.5}$ estimates. Across all outcome categories where OLS showed either null or marginally significant results, the IV coefficients are substantially larger in magnitude and statistically significant. $PM_{2.5}$ is now positively and significantly associated with total accidents in columns 1 and 5, aggressive driving in columns 2 and 6, and driver error in columns 3 and 7, while the substance/other as our placebo test remains insignificant in columns 4 and 8. The estimates are also closer in magnitude to the ones found in the previous literature in Sager (2019).

Table 4. Second Stage Results

Panel A. Estimates Results Using Hyperbolic Sine Transformation				
	(1) Accidents	(2) Aggressive	(3) Error	(4) Sub/Other
$PM_{2.5}$	0.00317**	0.00220*	0.00188*	0.000870
	(0.00144)	(0.00112)	(0.00110)	(0.000926)
N	195958	195958	195958	195958
KP F	21.90	21.90	21.90	21.90
F	9.395	6.875	2.760	12.11
Panel B. Estimates Results Using Log Transformation				
	(5) Accidents	(6) Aggressive	(7) Error	(8) Sub/Other
$PM_{2.5}$	0.00262**	0.00176**	0.00149*	0.000689
	(0.00114)	(0.000878)	(0.000852)	(0.000718)
N	195958	195958	195958	195958
KP F	21.90	21.90	21.90	21.90
F	9.430	6.895	2.836	12.05

Note: All regressions outcomes are transformed by the hyperbolic sine transformation or the log transformation of log(Y+1). All equations use controls for weather variables such as temperature, humidity, precipitation, wind speed, atmospheric pressure and wind direction. All equations employ region, route-day-week and month-year fixed effects. Standard errors are clustered two-way clustered at the region-date level. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

This pattern with OLS estimates consistently smaller than IV estimates can be generate as the endogeneity that air pollution has since it is correlated to unobservable factors such as economic activity or daily changes in human activity. The IV results therefore suggest that the OLS estimates understate the true causal effect of air pollution on accident risk.

Vehicle Heterogeneity

Table 5. Vehicle Heterogeneity

Panel A. Vehicle Heterogeneity			
	(1)	(2)	(3)
	Car	Bike	Large Vehicle
$PM_{2.5}$	0.00223*	0.00150**	0.00203**
	(0.00123)	(0.000579)	(0.000783)
N	195958	195958	195958
F	10.24	9.391	7.705
Panel B. Aggressive Accidents by Vehicle			
	(4)	(5)	(6)
	Car	Bike	Large Vehicle
$PM_{2.5}$	0.00161*	0.000661	0.00110**
	(0.000895)	(0.000473)	(0.000493)
N	195958	195958	195958
F	7.063	4.614	5.497
Panel C. Error Accidents by Vehicle			
	(7)	(8)	(9)
	Car	Bike	Large Vehicle
$PM_{2.5}$	0.00119	0.00126**	0.000247
	(0.000749)	(0.000492)	(0.000663)
N	195958	195958	195958
F	2.934	9.009	2.281
Panel D. Substance and Other Causes of Accidents by Vehicle			
	(10)	(11)	(12)
	Car	Bike	Large Vehicle
$PM_{2.5}$	0.000728	-0.000140	0.000770
	(0.000714)	(0.000337)	(0.000510)
N	195958	195958	195958
F	11.83	1.037	8.676

Note: All regressions outcomes are transformed by the hyperbolic sine transformation. All equations use controls for weather variables such as temperature, humidity, precipitation, wind speed, atmospheric pressure and wind direction. All equations employ region, route-day-week and month-year fixed effects. Standard errors are clustered two-way clustered at the region-date level. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

We extend the analysis along two additional dimensions simultaneously: vehicle type and fault classification. First, we present the heterogeneity analysis for our three vehicle categories which are cars (non-commercial passenger vehicles), bicycles (any two-wheeled transport), and large vehicles (trucks and buses). Second, we also combined the vehicles classes with the accident cause group (aggressive driving, driver error, and substance or other causes). This decomposition allows us to assess whether the effects of $PM_{2.5}$ vary according to the type of vehicle used or distributed broadly, and whether pollution affects the behavior of the driver differently depending on the vehicle involved.

We present the results of the second stage regression employing the thermal inversions as instrument for the first stage in table 5. Total accidents involving cars in column 1, bicycles in column 2, and large vehicles in column 3 all show significant positive $PM_{2.5}$ coefficients. Among fault-type interactions, car aggressive in column 4, large vehicle aggressive in column 6, and bicycle error in column 8 is statistically significant, while the remaining fault-type reach significance levels. This is important, especially for the accidents driven by substance or other causes, which is our placebo test in columns 10 to 12 remaining consistent with previous results.

The emergence of significant bicycle effects is particularly noteworthy: Cars and large vehicles are more likely to exhibit aggressive behavior or risky maneuvers because drivers might feel a larger sensation of security. While cyclists, are more vulnerable and exposed, are affected primarily through errors in judgment and coordination rather than deliberate aggressive actions due to the risk involved in those types of vehicles while engaging in risk adverse maneuvers.

Age and gender heterogeneity

We then investigate whether the relationship between $PM_{2.5}$ and traffic accidents varies across driver age groups, estimating separate regressions for seven age brackets: under 18, 18–24, 25–34, 35–44, 45–54, 55–64, and 65 and above. The regression results are shown in table 6. Younger drivers may be more prone to risk-taking behavior that is amplified by pollution-induced cognitive impairment. Middle-aged drivers, who constitute the bulk of daily commuters, may face the highest

absolute exposure and therefore exhibit the strongest pollution effects in terms of total accident counts. Older drivers may be physiologically more sensitive to pollution-induced health effects, even at lower concentrations.

Table 6. Age Heterogeneity

	Age Groups						
	(1) 0–17	(2) 18–24	(3) 25–34	(4) 35–44	(5) 45–54	(6) 55–64	(7) 65+
$PM_{2.5}$	0.000277**	0.000604	0.000920	0.00256***	0.00137**	0.000288	0.00105**
	(0.000126)	(0.000509)	(0.000803)	(0.000930)	(0.000679)	(0.000702)	(0.000415)
N	195,958	195,958	195,958	195,958	195,958	195,958	195,958
F	1.86	1.57	6.56	9.24	6.14	5.95	3.60

Note: All regressions outcomes are transformed by the hyperbolic sine transformation. All equations use controls for weather variables such as temperature, humidity, precipitation, wind speed, atmospheric pressure and wind direction. All equations employ region, route-day-week and month-year fixed effects. Standard errors are clustered two-way clustered at the region-date level. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

The IV estimates $PM_{2.5}$ shows that air pollution has significant effects on accidents for multiple age groups. The most striking finding is the significance of $PM_{2.5}$ for the youngest cohort of ages 0–17 in column 1, which is unexpected given the low baseline accident rates for this group and suggests that even infrequent young drivers are meaningfully affected by pollution exposure when they do drive. Significant effects also emerge for middle-aged drivers in ages of groups of 35–44 and 45–54 in columns 4 and 5, consistent with the high driving frequency and commuting intensity of these groups generating substantial pollution exposure. Older drivers aged 65 and above also show a significant positive IV coefficient, consistent with known physiological sensitivity to air pollution in older populations. In contrast, the 18–24 and 55–64 groups show positive but imprecisely estimated $PM_{2.5}$ effects.

We then examine gender heterogeneity in the relationship between $PM_{2.5}$ and traffic accidents, crossing total accidents by gender with three fault types, aggressive driving, driver error, and substance related or other causes. This decomposition is motivated by a substantial literature documenting gender differences in driving behavior, risk tolerance, and sensitivity to environmental stressors. Men are consistently found to

drive more aggressively and to be involved in a disproportionate share of serious accidents, while women tend to exhibit more cautious driving styles. If $PM_{2.5}$ impairs self-regulation, impulse control, or attentional capacity, it may amplify gender-typical patterns, producing differential effects across fault types.

Table 7. Gender Heterogeneity

Panel A. Female				
	(1)	(2)	(3)	(4)
	All	Aggressive	Error	Sub/Oth
$PM_{2.5}$	0.00133**	0.00102***	0.000497	0.000183
	(0.000543)	(0.000357)	(0.000360)	(0.000230)
N	195,958	195,958	195,958	195,958
F	7.29	4.98	1.89	9.31
Panel B. Male				
	(5)	(6)	(7)	(8)
	All	Aggressive	Error	Sub/Oth
$PM_{2.5}$	0.00306**	0.00198*	0.00175*	0.000782
	(0.00140)	(0.00109)	(0.000995)	(0.000912)
N	195,958	195,958	195,958	195,958
F	8.99	6.48	3.52	11.58

Note: All regressions outcomes are transformed by the hyperbolic sine transformation. All equations use controls for weather variables such as temperature, humidity, precipitation, wind speed, atmospheric pressure and wind direction. All equations employ region, route-day-week and month-year fixed effects. Standard errors are clustered two-way clustered at the region-date level. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

$PM_{2.5}$ is positive and statistically significant for total accidents among both female in column 1 and male drivers in column 5, confirming that pollution effects are not confined to one gender. Among fault-type interactions, male aggressive driving in column 6, female aggressive driving in column 2, and male driver error in column 7 are all significant, while female driver error in column 3 is positive but imprecise. While neither gender shows no significant effects for substance related or other causes in columns 4 and 8, consistent with the placebo interpretation from earlier tables.

$PM_{2.5}$ thresholds

Table 8. $PM_{2.5}$ thresholds

Panel A. Threshold 1				
	(1) Accidents	(2) Aggressive	(3) Error	(4) Sub/Other
$PM_{2.5}$ 15 μg/m³	0.0792** (0.0387)	0.0550* (0.0327)	0.0471* (0.0268)	0.0218 (0.0242)
N	195,958	195,958	195,958	195,958
F	10.07	7.04	3.30	12.30
Panel B. Threshold 2				
	(5) Accidents	(6) Aggressive	(7) Error	(8) Sub/Other
$PM_{2.5}$ 20 μg/m³	0.0967** (0.0483)	0.0672* (0.0379)	0.0575* (0.0340)	0.0266 (0.0288)
N	195958	195958	195958	195958
F	8.967	6.421	3.332	12.21
Panel C. Threshold 3				
	(9) Accidents	(10) Aggressive	(11) Error	(12) Sub/Other
$PM_{2.5}$ 35 μg/m³	0.234* (0.127)	0.163** (0.0813)	0.139 (0.100)	0.0644 (0.0656)
N	195958	195958	195958	195958
F	8.525	6.021	2.274	12.06

Note: All regressions outcomes are transformed by the hyperbolic sine transformation. All equations use controls for weather variables such as temperature, humidity, precipitation, wind speed, atmospheric pressure and wind direction. All equations employ region, route-day-week and month-year fixed effects. Standard errors are clustered two-way clustered at the region-date level. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 8 presents robustness checks using alternative thresholds for $PM_{2.5}$ intensity. The first panel uses a binary indicator for inversions exceeding the 15 μg/m³ threshold, yielding positive and significant effects on total accidents, aggressive driving, and driver error, while substance/other causes remain insignificant, consistent with the main results. The results stay consistent when employing higher thresholds of 20 μg/m³ and 35 μg/m³, and the coefficients are slightly larger in magnitude but qualitatively identical, confirming that the main findings are not sensitive to the inclusion of weather covariates. The substance/other category remains insignificant across all three panels, reinforcing the placebo interpretation. Overall, these results

confirm that the main findings are robust to alternative definitions of inversion intensity and are not driven by weak or marginal increases in $PM_{2.5}$ concentrations.

Accidents timing

Figure 1. Timming of the effect of pollution

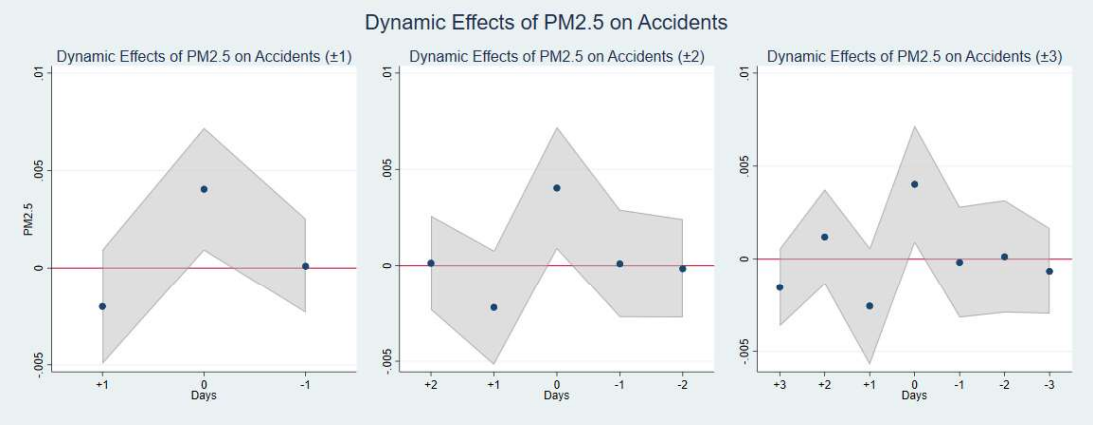


Figure 1 presents a dynamic specification including leads and lags of $PM_{2.5}$ exposure up to three days before and after the current day, serving as a falsification test for the identifying assumption using the hyperbolic sine transformation for the accident's outcomes. Across all three windows (±1, ±2, and ±3 days), only the contemporaneous effect (day 0) is positive and precisely estimated, while all leads and lags are small, oscillate around zero, and fall within the confidence band. The absence of significant lead effects is particularly important, it rules out the possibility that inversions are correlated with pre-existing trends in accidents, supporting the validity of the exclusion restriction. The absence of significant lag effects suggests that the impact of pollution on accident risk is immediate and does not persist beyond the day of exposure, consistent with a short-lived physiological impairment mechanism rather than a cumulative or chronic exposure channel. The results are also consistent with previous literature as Sager (2019) suggest in a similar dynamic model.

Other robustness check

Table 9. Alternative Robustness Check

Panel A. Excluding Peak Burning Season				
	(1) Accidents	(2) Aggressive	(3) Error	(4) Sub/Other

$PM_{2.5}$	0.00442***	0.00393***	0.00156	0.00152
	(0.00164)	(0.00129)	(0.00124)	(0.00115)
N	146554	146554	146554	146554
KP F	27.58	27.58	27.58	27.58
F	11.99	10.09	2.308	11.93
Panel B. Excluding 5% Most Congested Routes				
	(5) Accidents	(6) Aggressive	(7) Error	(8) Sub/Other
$PM_{2.5}$	0.00366**	0.00235**	0.00236*	0.000811
	(0.0017)	(0.00111)	(0.00125)	(0.000859)
N	175154	175154	175154	175154
KP F	21.59	21.59	21.59	21.59
F	5.502	5.502	5.502	5.502

Note: All regressions outcomes are transformed by the hyperbolic sine transformation. All equations use controls for weather variables such as temperature, humidity, precipitation, wind speed, atmospheric pressure and wind direction. All equations employ region, route-day-week and month-year fixed effects. Standard errors are clustered two-way clustered at the region-date level. Statistical significance is indicated by * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

Table 9 presents robustness checks decomposed by fault type across two sample restrictions. Columns 1–4 exclude peak burning season months (July–September) and columns 5–8 exclude the top 5% most congested routes. Across both restrictions, total accidents in columns 1 and 5 remain positive and significant, with coefficients of 0.0044 and 0.0037 respectively, closely in line with the main specification. Among fault types, aggressive driving in columns 2 and 6 is significant in both restricted samples, while driver error in columns 3 and 7 reaches significance only in the congested routes sample, and substance/other causes in columns 4 and 8 remain insignificant throughout, replicating the placebo pattern from the main results. The stability of the $PM_{2.5}$ coefficient across these two very different sample restrictions, combined with Kleibergen-Paap F statistics of 27.6 and 21.6 well above the weak instrument threshold, confirms that the main findings are not driven by burning season confounding or by residual congestion in high-traffic routes.

Conclusion

This chapter provides causal evidence that ambient air pollution increases traffic accident risk in Brazil and identifies the behavioral channels through which this effect operates. Using thermal inversions as an instrument for daily $PM_{2.5}$ concentrations, we find that a one standard deviation in $PM_{2.5}$ concentrations (around 10 $\mu g/m^3$) increase in pollution raises total accidents by approximately 3 percent, with effects driven by aggressive driving and cognitive errors rather than substance-related or mechanical causes. This pattern is consistent across vehicle types, age groups, and genders, and holds under a range of robustness checks including alternative inversion thresholds, exclusion of burning season months, and restriction to less congested routes.

The fault-type decomposition is the central contribution of this chapter. Prior work by Sager (2019) and Braun and Villas-Boas (2023) established that pollution raises accident risk through behavioral rather than traffic volume channels but could not determine whether the mechanism was cognitive impairment, increased aggression, or both. Our results show that both channels are active: $PM_{2.5}$ significantly increases accidents attributed to aggressive driving in a larger way to driver error, while leaving substance-related causes unaffected. The dynamic specification further confirms that these effects are immediate, concentrated on the day of exposure with no significant leads or lags, pointing to acute physiological impairment rather than cumulative exposure as the operative mechanism even in low pollution scenarios below the recommended standards.

The heterogeneity results add further texture. Among vehicle types, cars and large vehicles show effects concentrated in aggressive behavior, while cyclists are more affected through errors in judgment and coordination, a pattern consistent with the different risk profiles and protective environments of these road users. Among age groups, the strongest effects emerge for middle-aged drivers (35–54), who face the highest commuting exposure, and for drivers aged 65 and above, consistent with known physiological sensitivity to pollution in older populations. The result for the youngest cohort (under 18) is also notable, suggesting that even occasional young

drivers are meaningfully affected when they do drive. Gender effects predicting stronger male responses than the female counterparts by a slim margin.

These findings have direct policy relevance for Brazil. The country has made substantial investments in road safety enforcement and infrastructure, yet road deaths remain persistently high relative to high income countries. Our results suggest that air quality management is an underappreciated lever for road safety policy: reducing $PM_{2.5}$ concentrations through vehicle emission standards, urban traffic management, or industrial regulation would generate road safety co-benefits beyond the well-documented health gains. This is particularly relevant in a context like Brazil where pollution exposure is high, vehicle fleets are older, and road safety margins are already thin.

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