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1 Introduction

According to the World Health Organization (WHO, 2017), atmospheric air pollution is a major threat for public health in cities, affecting three billion people around the world. There is overwhelming evidence showing how pollutants such as ozone (O3), carbon monoxide (CO), nitric oxide (NO), particulate matter (PM) and other pollutants are responsible for deteriorating human health. For example, it has been showed that higher air pollution increases lung related diseases (Gillingham and Huang, 2021), cardiovascular diseases (Gupta, 2021; Slawsky et al., 2021), mental disorders (Ordoñez, 2020) and mortality rates (Deryugina et al., 2019), rising health care costs for individuals and the health care systems. In total, health related costs of air pollution (mainly by PM2.5) have been estimated, globally, in around 6.1% of the Gross Domestic Product (GDP), equivalent to $8.1 trillion USD (World Bank, 2016). In developing countries, the situation is more dire due to a combination of factors like lack of environmental regulation and enforcement, use of low quality fuel, fast growth in the number of cars and

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motorcycles, and deficient public transportation systems. The World Bank (2016) shows that, while the cost of air pollution is estimated in 1.7% of GDP in North America, in Latin America the cost is around 3.4% of the GDP. Particularly, in Colombia, the *Departamento Nacional de Planeación* (DNP, 2017) calculates the damage cost for urban air pollution in 1.93% points of Colombian GDP.

The adverse effects of pollution on academic performance are also worrisome given the influence of education on economic mobility, labor market outcomes and economic growth as highlighted by Bharadwaj et al. (2017); Graff-Zivin and Neidell (2013). Higher levels of air pollution make more likely students will miss classes, by affecting their health, as well as harming their capacity to learn by hampering their cognitive development (Persico and Venator, 2021). Previous studies in developed countries have shown how exposure to air pollution negatively affect different education and human capital formation outcomes (Heissel et al., 2022; Kweon et al., 2018; Sunyer et al., 2015; Wang et al., 2009; Appatova et al., 2008). Despite all previous evidence, less is known about the effects of pollution on academic achievement in developing countries, and specially at a very local urban scale. The difficulties to obtain evidence in developing countries originate in part due to an absence of data about urban pollution levels. This lack of evidence hinders the promotion of effective strategies that limit the harmful effects of pollution and improve education in a context of poor academic performance (Cebrián et al., 2019).

In this paper, we estimate the effect of air pollution on academic achievement at a very local urban scale using the number of traffic accidents as a proxy of air pollution emissions, taking advantage of the highly granular public available information of motor-car accidents for the city of Medellín, Colombia. Previous studies in the developed world rely on proximity to highly polluting sources to gauge the effect on academic performance such as heavy traffic and highways, due to the exacerbated use of fossil fuels for urban transportation. Nonetheless, no study has centered on car accidents as a particular source of air pollution. Accidents can worsen levels of air pollution through its impact on traffic congestion. Accidents lead to slower traffic speeds and to a more frequent process of starting, accelerating and braking vehicles, thus leading to greater combustion of fuels and higher levels of pollutants in the air. This can be specially true in developing countries where the prevalent use of motorcycles, old cars, and reckless drivers make traffic accidents more frequent, with drastic consequences in terms of injuries and deaths. For example, according to data from OCDE [1], Colombia has an average of 10.8 road fatalities per 100,000 inhabitants, a number substantially higher than the rate in developed countries.

Moreover, in Colombia, car insurance requirements can make the congestion consequences of accidents much worse. Since car owners are only required to buy insurance for accident-related injuries, drivers usually remain at the collision point without moving their vehicles, waiting for traffic police to determine who is responsible, heavily reducing mobility. Just in the capital city of Bogotá, car accidents generate the equivalent of 335 million hours lost on congestion per year (Sánchez-González et al., 2021). Focusing on traffic accidents can expand the scope of strategies to control air contamination. If a strong correlation between accidents and pollution exists, authorities can define protocols to decrease the impact of accidents on pollution. It can also help to better understand the effects of air pollution at a local scale in cities of developing countries. In developing countries, pollution and congestion data is scarce, limited to particular cities for a small number of locations inside each city. In comparison, accident data with high frequency and high spatial granularity can be easily obtained. Thus, by using the number of traffic accidents as a proxy measure for pollution, the effects of pollution on different outcomes can be identified at a local scale.

To quantify the effects of pollution on academic performance, we first provide evidence in favor of the use of accidents as a proxy measure of mobile air pollution at small local areas. Then, using a Two Way Fixed Effects (TWFE) identification strategy, we approximate the causal effect of air pollution on academic achievement. We use data of vehicles accidents, air pollution emissions, high schools and students' academic results for the city of Medellín, the second largest city in Colombia. Our results show a positive relation between car accidents and air pollution in the city. We also provide evidence of the negative effect of accidents on

[1] Road Safety Anual Report, OCDE 2021; from https://www.itf-oecd.org/sites/default/files/docs/irtad-road-safety-annual-report-2021.pdf

the academic performance of students; this effect is larger when accidents involve motorcycles or injured and dead people. We also explore differences by high school groups and student gender. The document is organized as follows: first we present a literature review, then we present a section of context, next we present data sources and descriptive statistics; then we present the empirical strategy and results, and finally we present a section with the discussion and conclusions.

2 Context

Medellín offers an interest case to study the effects of air pollution on academic performance at local scale. With 2.4 million people and an area of 382 km^2, Medellin is the second largest city in Colombia[2] and one of the most densely populated cities in Latin America. In the last 10 years, the city has experienced an accelerated growth in the number of vehicles and land developments which, together with the geographical and weather conditions of the city, make Medellin one of the most polluted cities in the continent. According to the 2020 Quality of Life Report of *Medellin Como Vamos* (Meneses et al., 2020) in Medellín and its metropolitan area, the annual PM10 concentrations range between 34 and 50 mg/m3, levels way above of the 20 mg/m3 level recommended by the WHO (2017). Similarly, annual averages of PM 2.5 concentrations range between 19 and 51 mg/m3, surpassing the WHO guidelines target of a maximum of 10 mg/m3. Additionally, the air quality index for PM2.5 in the center of the city was classified as good for 0% of all days in 2019 and only 2% in 2018.

In response to these circumstances, the Comprehensive Air Quality Management Plan for the AMVA (2017-2030) was designed as an institutional framework to mitigate the problem of air pollution. Given how vehicle emissions can account for up to 85% of all air pollution for big cities like Medellín (CONPES, 2018), the strategies proposed include abandoning highly polluting modes of transportation by adopting cleaner technologies, encouraging the use of massive transport systems and promoting active mobility in the city. No particular guideline was

[2]Medellín is the biggest in population of ten cities that conform the *Área Metropolitana del Valle de Aburra* called AMVA. We only study Medellín given data availability.

emitted regarding traffic accidents, despite the high accident rate in the city and its influence in the mobility.

In Colombia, and particularly in Medellín, car accidents can be considered a major source of gas emissions. The number of motorcycles and reckless drivers make traffic accidents highly frequent, originating traffic congestion and pollution. Importantly, the particularities of car insurance requirements in the country make the congestion consequences of traffic accidents much worse. According to current legislation, only the *Seguro Obligatorio de Accidentes de Tránsito* (SOAT) is mandatory for all vehicles. The SOAT covers all health expenses in the event of injuries like ambulance services, emergency care, hospitalization, medical treatments and even sick leave, for those involved in the accident. However, the SOAT does not cover the physical damages of vehicles involved in the accident and full coverage insurance is not required by law, leaving it up to the car owners to obtain it. This means that any type of vehicle accident can affect mobility for long periods of time. When a car crash occurs, it is common for drivers to remain at the collision point without moving their vehicles, waiting either for a negotiation on who pays for damages (specially if one or both of them don't have full insurance) or for traffic police to determine whose responsible, issue an infraction and a court appointment to dispute responsibilities and costs. Given this idiosyncrasy, it is highly likely that a vehicle accident will cause time delays, traffic jams, slower speeds and overall, lots of concentrated air emissions, even if there is no injured people involved in. [3] This peculiarity makes car accidents within cities in Colombia a good variable to measure, and partially explain, levels of mobile source air pollution.

3 Evidence from Academic Literature

Pollution emissions in general are considered a major problem in big populated cities. International institutions like the World Health Organization and the World Bank regularly report about the adverse effects on human health and the economic costs of pollution (WHO, 2017;

[3]New traffic regulations have been put in place in lately years (2022) that forbids vehicles to remain waiting unless medical attention is needed. The regulation aims to reduce waiting time of uninsured drivers, as well as it promotes drivers to buy full insurance.

World Bank, 2016). These reports are based on an ample set of academic literature that have analyzed the effects of pollution on health outcomes, showing how exposure have direct effects on increasing lung related diseases (Gillingham and Huang, 2021; Chang et al., 2009), cardio-vascular diseases (Gupta, 2021; Slawsky et al., 2021), mental disorders (Ordoñez, 2020; Chen et al., 2018) and certain disabilities (Bishop et al., 2018; Volk et al., 2011). Some studies focus on the impact of pollution at early stages such as exposure in-utero or infants (Pons, 2022; Gehring et al., 2014; Currie and Walker, 2011; Currie and Neidell, 2005; Currie et al., 2009). Studies have considered different pollutants such as lead, radiation and all types of airborne contaminants related to those effects, often analyzing CO, PM2.5, PM10, as well as NO2, SO2, O3 and Volatile Organic Compound.

Another common theme in the literature regards academic performance and other learning outcomes, directly related to health problems caused by pollution emissions. Persico and Venator (2021) highlights two main mechanisms in which exposure to air pollution affects academic performance: (i) being exposed to air pollution affects health, thus students are more likely to miss classes; and (ii) being exposed to air pollution affects cognitive development, harming the child's capacity to learn and, therefore, his academic results. For people living or studying in areas with high levels of pollution, it has been proved that being exposed worsens their results in standardized tests (Zweig et al., 2009), cognitive performance (Lavy et al., 2014) and human capital formation (Graff-Zivin and Neidell, 2013; Currie et al., 2014). In similar fashion to the literature on health, negative effects of pollution on academic performance have been found due to exposure during in-utero (Sanders, 2012; Bharadwaj et al., 2017; Black et al., 2019) or at early ages (Aizer et al., 2018).

Traffic as source of air pollution emissions has been a major focus of analysis in academic literature looking for effects on both in health and education. For instance, Alexander and Schwandt (2019) find that car pollution impact infant and child's health by using car mobility, car density and traffic influx as predictors of mobile air pollution. While Currie and Walker (2011) estimate effects on birth outcomes using mothers living two kilometers around a highway that changed a paid toll to an electronic toll reducing levels of air pollution emissions.Knittel et al. (2016) use total traffic flow and average speed to estimate the impact of air pollution on infant mortality by being exposed to high levels during the first week of life, employing panel fixed effects and instrumental variables. Simeonova et al. (2021) take advantage of an environmental imposition for car congestion in downtown Stockholm to study the consequences on asthma for children residing in Stockholm's inner city using a panel with fixed effects. In addition, Appatova et al. (2008); Kweon et al. (2018) highlight how proximity to highways or industries are associated to lower academic performance. Lastly, Hollingsworth et al. (2020) examines how living close to NASCAR tracks impacts negatively academic performance in students. Authors exploit a natural experiment, where a sudden change in policy eliminated lead concentrations in fuel commonly used in NASCAR races, allowing them to compare individuals living near racetracks before and after the introduction of the new law. Other pollution sources inspected by these studies include power plants, airports and ports. Despite all the research concentrating on heavy traffic, highways or other sources connected to motorized vehicles, to the best of our knowledge, there is no work exploring car accidents as a source of air pollution to study its effects on educational achievement or health.

Furthermore, there is a considerable gap in the amount of evidence in developed countries, specially the United States, and developing countries. Developing countries acquire great importance given their higher pollution levels compared to advanced economies. Adding to this, evidence in developed countries indicate that the negative effects of pollution is larger in racial minorities, lower income and other vulnerable populations (Pons, 2022; Gillingham and Huang, 2021; Halliday et al., 2019) making it imperative to research developing countries given that disadvantaged people make up a higher percentage of their population.

4 Data and Variables

For test scores, *Instituto Colombiano para la Evaluación de la Educación* (ICFES) provides information of the mandatory standardized test for students graduating high school in Colombia, called Saber 11. For each student, information includes scores for the areas of Mathematics, Biology, Chemistry, Physics, Social Sciences, Spanish, English and the overall score. Although

ICFES tests all areas, only Math, Spanish and English have a high percentage of valid information (More than 99%).[4]. In total, we have 228,587 students across 376 high schools and 10 years of exams from 2007 to 2017. It's important to note that the scoring methodology changed in 2014; thus, we standardize the scores using each year mean and standard deviation to make scores comparable across time.[5]

On top of scores, ICFES offers information on students characteristics, family characteristics and some school features, mostly related to funding and gender isolation. Since data from ICFES also includes the address of the students' high school, we geo-codify to obtain the coordinates, localizing 376 out of all 385 high schools in the city. To complement the school data, the *Departamento Adminisitrativo Nacional de Estadistica* (DANE) offers information regarding characteristics of high schools, updated yearly. This data includes important features such as proportion students-teachers, number of groups at the eleven grade, higher degree of teachers, total of student by eleven grade, etc.

Pollution emissions were measured by *Red Calidad del Aire* (REDAIRE) from 2006 to 2013, and by *Sistema de Alerta Temprana del valle de Aburrá* (SIATA) from 2014 onward. Both institutions recorded hourly data of different pollutants, however, inconsistently. Out of 16 stations, 9 recorded data for CO at any moment of time, with only 3 recording data in 2017. A similar situation is faced regarding O3 and PM10. From 2006 to 2013, 6 monitoring stations were found throughout the city, but only 3 recorded information in a constant manner. After 2014, more monitoring stations were added measuring new pollutants such as Nitrogen Oxides (NO, NO2 and Nox), and PM2.5 but with a large amount of missing data. In consequence, the available information lacks both time and spatial continuity, necessary to make any reliable inference. Nonetheless, we use available data to explore the relation between pollution and car accidents.

Even if pollution data were reliable, using air pollution emission levels measured from air quality monitors always rises a question about the measurement accuracy. There is no way to

[4]From 2007 to 2017, scores in other fields barely have 50% of data available.

[5]To standardize we use the formula: $Score_{it}^{Std} = \frac{Score_{it} - \overline{Score_t}}{SD_{Score_t}}$ where i is individual student and t is the exam. Then scores are read as deviations from the exam average.

know if the device is close to the sources of air pollution, or if it is just close enough to measure less concentrated emissions. In this sense, proximity to traffic can be taken as a 'closer' measure of air pollution emissions coming from mobile sources. However, there is no information of vehicle density. To overcome this issue, we use car accidents as our proxy. The *Secretaría de Movilidad de Medellín* (SMM) collects information of traffic accidents occurred in Medellín. From 2004 onwards, information includes day and hour of accident, type of vehicle involved (Car, Motorcycle, Bus), accident type (Crash, Runover), sex and age of drivers and severity (Involving property damages, injured or dead people). The dataset also includes address of the accident at the block corner. We acknowledge this minor error in measurement, but given how small and random the error in distance is, we consider that it does not represent a threat to identification.

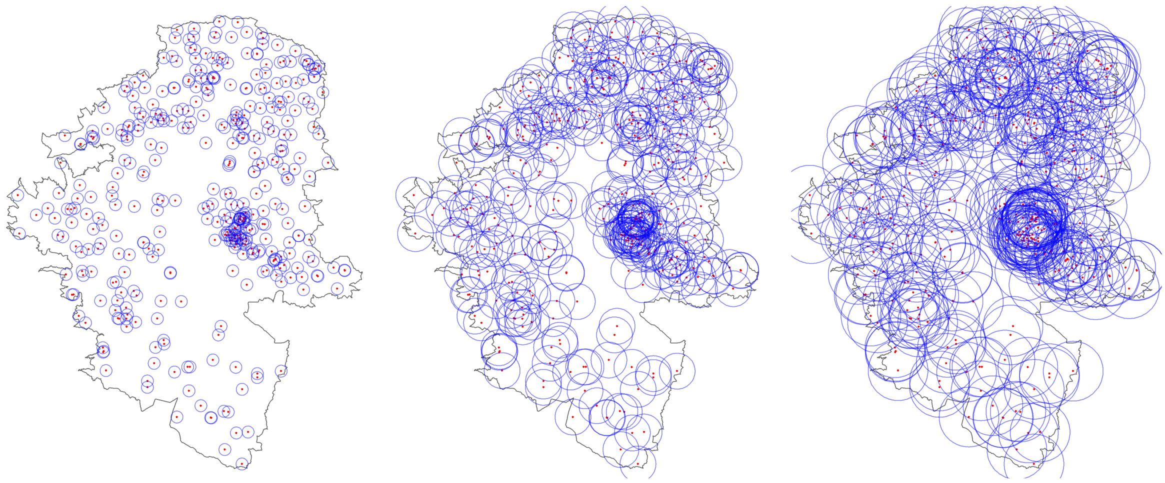
To calculate our treatment variable, we count all accidents in a buffer around each school for every day and compare it with the annual daily mean in all schools. Next, we calculate the percentage of days where the number of accidents was above this mean in a period before the exam date. Formally,

$$CarAcc_{hp_t}^{Std} = \frac{\sum_{day=1}^{n_{p_t}} I(CarAcc_{hday_p} > \overline{CarAcc_{year_p}})}{n_p} \tag{1}$$

where sub-indexes h and p are high school-buffer and period before the exam date, I is an indicator variable that takes the value of 1 when the accidents $CarAcc$ around h is above the annual average of daily accidents inside all high school-buffer; and n_p is the number of days in p. To check how effects vary with different accidents, we focus on 3 versions of this variable, one accounting for all accidents, one for accidents that resulted in injuries or death and one that only accounts for accidents involving a motorcycle.

There is no theory to guide a choice of distance where accidents or pollution are relevant. Previous studies have defined different areas of influence, ranging from 100 mts up to a mile (1609 mts) (Van-Vliet et al., 1997; Appatova et al., 2008; Kweon et al., 2018). A visual inspection reveals that buffers bigger than 600 meters could be problematic because areas commonly overlap (Figure 1), representing a violation of the independence assumption, that could hinder the identification of the effect. Besides, 1000 mts in densely populated city is too big compared to the size of the city. We acknowledge that there high schools located close to each other, so they might share some accidents, but it is not the norm when looking at lower buffers. In any case, to observe spatial decay in the effect, we consider buffers from 200 to 600 mts. Also, to detect differences from exposure length, we consider periods of 6 and 12 months before the exam date.

Figure 1: **Buffers around High Schools**



(a) 200 mts (b) 600 mts (c) 1000 mts

We present descriptive statistics of variables of interest in Table 1 across different high school groups. We observe ample variability in standardized scores across high schools. For example, students from mixed-gender, public and afternoon shift high schools (columns MHS, PbHS and AfHS) are below the average in Mathematics, Spanish and English. We also observe differences in some average high school characteristics from single-gender high schools compared to others.

Table 1: **Average of characteristics from all data used by high school differentiated features**

		Gender		Funding		Shift	
Variables	AHS	SGHS	MHS	PvHS	PbHS	AfHS	MnHS
Student							
Math	0.00	0.43	-0.07	0.09	-0.06	-0.05	0.05
Spanish	0.00	0.50	-0.09	0.05	-0.03	-0.06	0.07
English	0.00	0.57	-0.10	0.24	-0.15	0.00	0.00
Gender (Male)	0.43	0.14	0.48	0.43	0.43	0.42	0.45
Family							
Income 7SMMLV	0.09	0.06	0.10	0.07	0.11	0.09	0.09
Father Primary	0.25	0.13	0.27	0.23	0.27	0.26	0.24
Father Secondary	0.36	0.34	0.36	0.29	0.40	0.33	0.39
Father Bachelor	0.11	0.23	0.09	0.19	0.06	0.12	0.10
Mother Primary	0.23	0.10	0.26	0.22	0.24	0.26	0.21
Mother Secondary	0.41	0.38	0.42	0.31	0.48	0.38	0.45
Mother Bachelor	0.11	0.23	0.09	0.19	0.06	0.12	0.10
School							
Academic	0.61	0.52	0.63	0.82	0.48	0.68	0.53
Technologic	0.06	0.06	0.06	0.04	0.08	0.05	0.08
Tech-Academic	0.32	0.41	0.31	0.14	0.44	0.26	0.39
Tuition 120k	0.07	0.05	0.08	0.14	0.03	0.08	0.07
Tuition 250k	0.08	0.19	0.06	0.20	0.00	0.07	0.08
Students/Teachers	26.8	22.4	27.6	26.6	26.9	28.9	24.6
Seniors/Students	28.9	34.6	27.9	18.7	35.0	26.3	31.8
Total Students	1516	1722	1479	1642	1442	1388	1658
Teachers Bachelor	36.28	44.30	34.85	49.40	28.49	35.65	36.98
Teachers Terciary	2.02	1.81	2.06	3.90	0.91	2.47	1.53
Accidents							
All (6mths)	117.8	144.9	113.2	154.4	95.0	126.7	107.8
Injured (6mths)	72.9	80.7	71.6	89.9	62.4	76.9	68.5
Motorcycle (6mths)	56.9	62.3	55.9	70.1	48.6	59.9	53.5
All (12mths)	226.2	279.6	217.0	295.5	183.0	242.7	207.5
Injured (12mths)	141.5	155.1	139.2	174.5	120.9	149.2	132.8
Motorcycle (12mths)	110.4	118.6	108.9	136.5	94.1	116.4	103.6
Observations							
High Schools	391	60	355	169	230	250	238
Students	294548	43283	251265	113182	181366	156516	138032

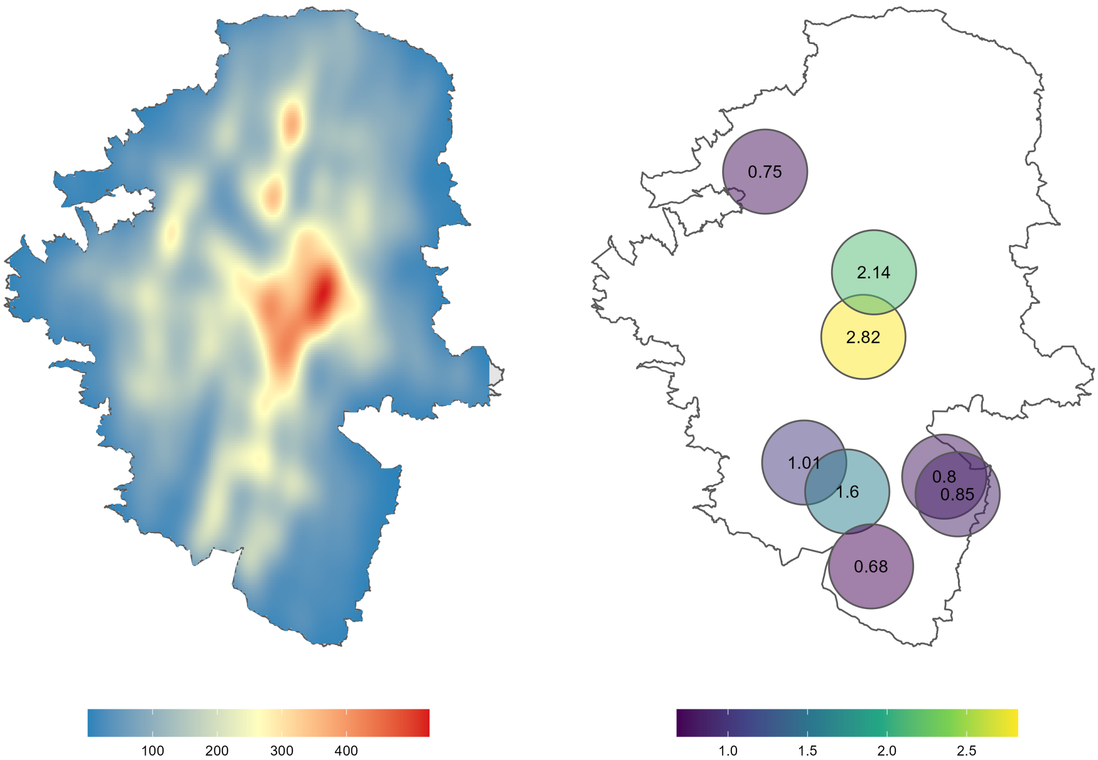
Note: Average of characteristics used in regression models.AHS: All high schools; SGHS: Single-gender high schools;MHS: Mixed-gender high schools; PvHS: Private High schools;PbHS: Public high schools; AHS: Afternoon-shift high school;MnHS: Morning-shift high schools

5 Car accidents as a proxy for Air Pollution

Mobile air pollution has been deemed as a negative factor for human health and education. Using traffic as a proxy of air pollution, researchers have used different ways to analyze its harmful effects, directly measuring traffic density with cameras at traffic lights and electronic tolls or indirectly using proximity to roads and highways. Differing from previous studies, we use car accidents as a proxy of air pollution. In big cities, car accidents are a major source of gas emissions, by causing or worsening traffic congestion, specially when people are injured in the accident. Despite inconsistencies in the available pollution data, we explore this relationship to gauge how good of a proxy car accidents is.

Figure 2 compares car accident density and CO pollution in Medellin. We observe that, there are more accidents in areas with busy streets, mostly related to commerce areas such as downtown Medellin and the main corridors connecting the city, such as the *Avenida Regional* running south-north (Figure 2a). Looking at air pollution levels, the same areas coincide with higher CO pollution readings from the Air Quality monitors (Figure 2b).

Figure 2: Spatial Distribution of Car Accidents and Air Pollution



(a) Accident Density (b) CO Pollution

Source: Own Elaboration. Accident Density from Kernel Density Estimation using data from 2017. CO Pollution shows the daily average around stations using all available data.

Nonetheless, to use car accidents as a good instrument for air pollution emissions, we have to consider not only CO but the main pollutants created by gas engines (Benmarhnia et al., 2015). Nriagu (2019) lists the pollutants produced by combustion engines, and abrasion of tires or brakes: carbon monoxide (CO), sulfur dioxide (SO2), nitrogen oxides (NOx), ozone (O3), volatile organic compounds (VOC), aromatic hydrocarbons (PAH) and particulate matter (PM) of different sizes. Using the daily [6] pollution average and the number of accidents occurring around the air quality monitors, we proceed to estimate pooled and two-way fixed effects models for the CO, PM10, PM2.5, NO2 and O3. Other pollutants such as SO2 were only recorded for a few days during 2006 to 2009, lacking enough data to estimate. We also did not find data on

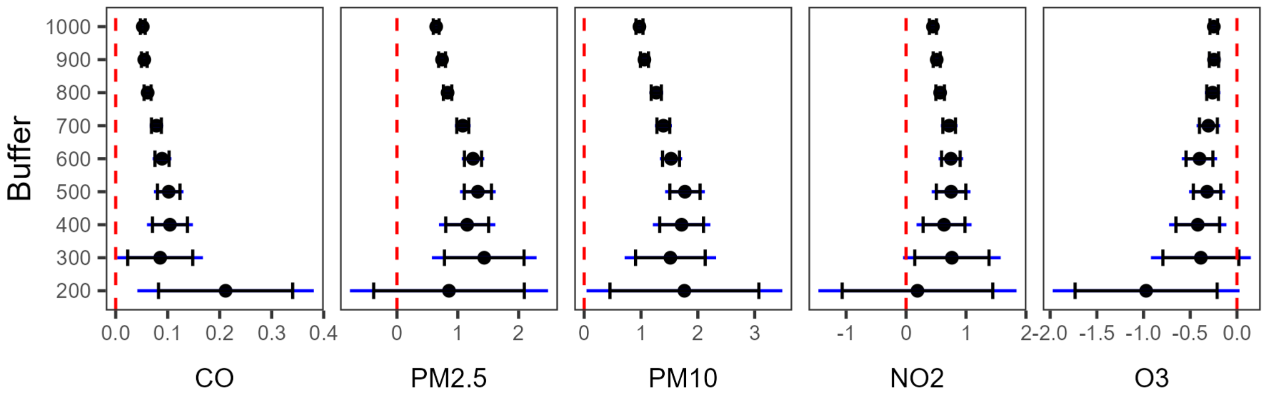
[6] Aggregating pollution data in periods larger than 1 day (such as the 6 and 12 months used in the main regression), posed a challenge given the amount of missing data. causing problems to obtain accurate averages. For example, in any given month, there is only data available for less than 12 days, making the aggregation potentially imprecise.

VOC or PAH to correlate with car accidents.

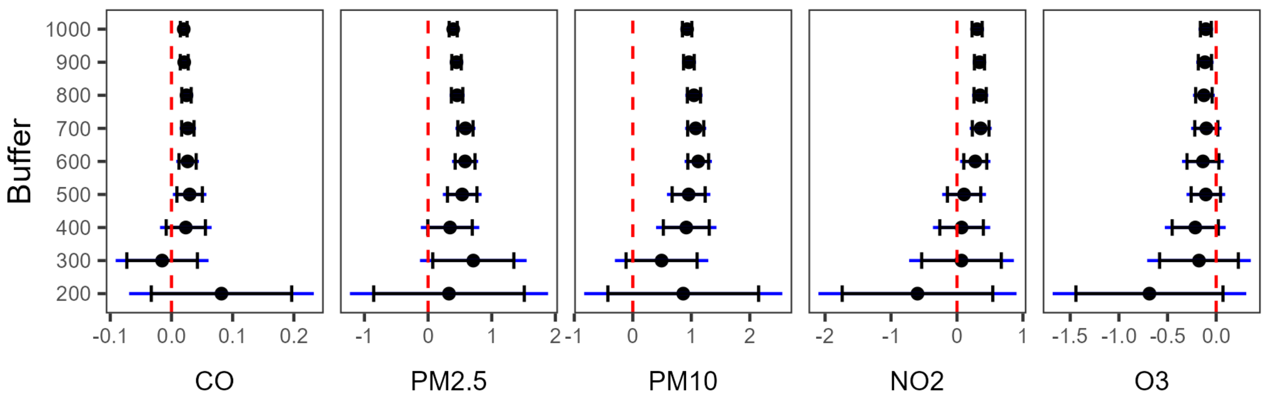
We find a positive and statistically significant coefficients for car accidents on CO, PM10, PM2.5 and NO2. In the fixed effects models, statistically significant results appear after 200 mts around the monitor, compared to the pooled estimator where we find positive correlation in all cases. Estimates for the smaller buffers are bigger than those for the largest buffers. The exception being O3, which shows a negative relation with car accidents, is an expected result since ozone is not entirely related to pollution emissions, as it depends largely on environmental conditions.[7] Results are consistent with the notion that car accidents are related to mobile pollution emissions.

[7]Such as solar radiation, nitrogen oxides (NOx), volatile organic compounds (VOC), and temperature (Nriagu, 2019).

Figure 3: Regression of Car Accidents on Pollution Emissions around Air Quality Stations. Daily Data.



(a) Pooled

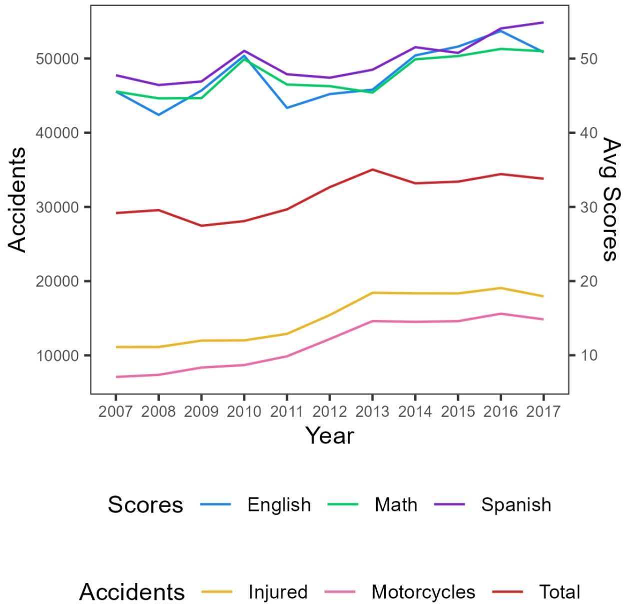


(b) Fixed Effects

Source: Own Elaboration. Using daily data from SIATA and Secretary of Mobility of Medellín 2007-2017. Confidence Intervals at 90% and 95%.

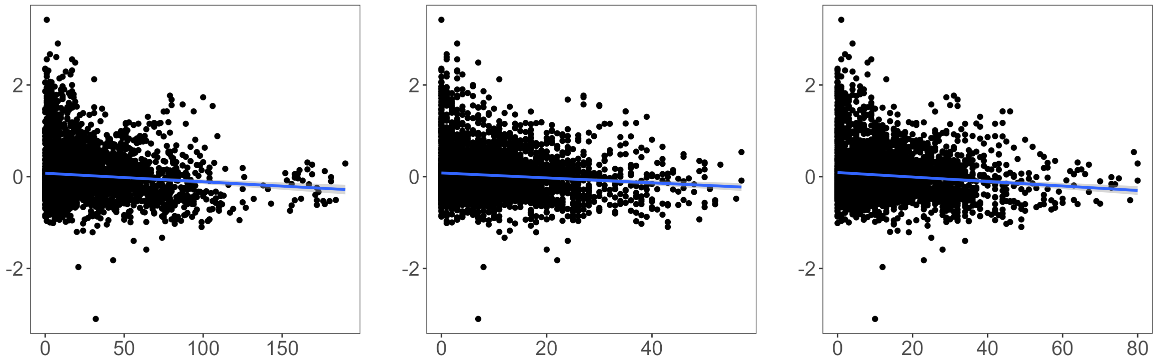
Having shown how accidents seem to correlate well to pollution, We focus on the relation between car accidents and test scores. Figure 4 graphs the temporal trends of car accidents and test scores during the time frame of our study for the city as a whole. Overall, we observe an increasing pattern in car accidents as well as an increasing trend on the three test scores. However, a closer inspection reveals that in the 2009-2011 period a decrease in car accidents coincide with an increase in test scores, while the opposite happens from 2011 to 2013. The same figure also plots accidents with motorcycles and injured people. Both series show a very similar behaviour, explained in good measure because bikers are the most exposed actors when an accident occurs, leading in general to a higher percentage of injuries and death.

Figure 4: Trend of Accidents and Test Scores Saber 11. Medellín 2007 to 2017.

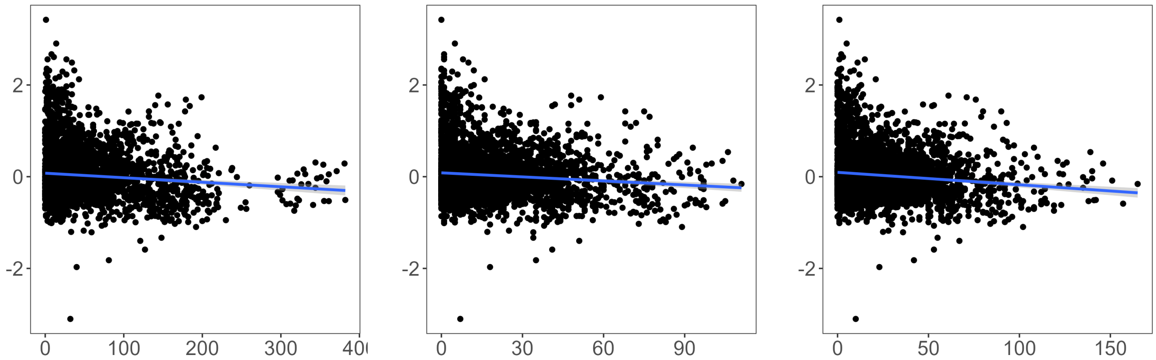


Finally, Figure 5 shows a set of scatter plots with a linear fit our standardized measures of the average high school math score and the different car accidents around 200 meters happening 6 and 12 months before the exams. These graphs exhibit a slightly negative linear association. Similar but steeper is the pattern for accidents only when bikes or injured people are taken into account. A similar result is observed when we consider different distances (Figure 9, Appendix A.2). It becomes apparent that educational attainment may be hampered by traffic collisions. Nonetheless, it's necessary to account for confounders before making a causal claim. In the next section, we present our identification strategy.

Figure 5: Correlation between Car Accidents and Average Test Scores in High Schools.



(a) Total - 6 Months (b) Motorcycles - 6 Months (c) Injured - 6 Months



(d) Total - 12 Months (e) Motorcycles - 12 Months (f) Injured - 12 Months

Source: Author's calculations. Y-axis represents Math Scores (as deviations from year mean) and the X-axis plots accidents (as number of days with accidents above year mean).

6 Identification Strategy

Our purpose is to shed light on the causal effect car accidents and air pollution has on student performance on the high school exit exam called Saber 11.

Lack of information is a common drawback when analyzing air pollution emissions. Available data is scarce both in space and time, introducing possible selection and measurement error biases. In its place, car accidents offers a good measure of mobile air pollution emissions at low geographical scales. However, pollution as well as car accidents are not random events, showing spatial concentration. This makes a basic correlation biased due to counfounding factors.

In our case, the main concern relates to the sorting of high schools, families and students across the city, where high quality schools and their students are located in high income areas with other amenities, such as low pollution, confounding the causal relation of interest. To overcome both observed and unobserved heterogeinity, we propose using a Two-Way Fixed Effects (TWFE) model defined as follows:

$$Score^{Std}_{iht} = CarAcc^{Std}_{hpt}\beta_1' + SC_{iht}\beta_2' + HSC_{ht}\beta_3' + \alpha_h + \gamma_t + \eta_{ht} \tag{2}$$

where $Score^{Std}_{iht}$ is the transformed score obtained by student i in high school h at exam t, $CarAcc^{Std}_{ht}$ is our defined version of car accidents that happened around h a period before t. In addition, SC_{iht} and HSC_{ht} are the student and high school characteristics (see Table 1). Lastly, time fixed effects (γ_t) control for unobserved changes among exams and other time varying but unit constant variables while high school fixed effects (γ_h) control for time-invariant unit heterogeneity and η_{ht} are errors clustered by high school. The TWFE model is well accepted to obtain causal estimates when the number of units is bigger than the time period as it is the case in the present study.

7 Results

We estimate equation 2 to understand whether students at high schools close to car accidents perform worse on the exit examination Saber 11 test. Table 2 shows results for baseline estimates. Results show car accidents having no effect on Spanish and English scores at any buffer or period whatsoever. Nevertheless, a negative statistically significant coefficient is observed for Mathematics at different buffers. An increase of one percent in days with high accidents is negatively associated with a reduction in 0.0007 standard deviations, below the average, in the score for mathematics (Column 1, Table 2). Results hold for accidents happening inside buffers from 200 to 400 mts and for the average of accidents twelve months before taking the test (columns 1 and 4 Table 2). The magnitude of the effect is progressively smaller at bigger buffers showing that it fades away with distance. Similarly, it is observed estimated coefficients are bigger when accidents are closer to the exam date. Further, coefficients for mathematics score and car accidents averaged for one week and one month show a bigger effect although not statistically significant (Columns 1 and 2, Part A, Table 4, Appendix A.1). After accumulated exposure from two months it appears a negative effect for 200 meters which also appears constantly for buffers 200 to 400 meters, after three months (Columns 3 to 6, Part A, table 4, Appendix A.1). Results show evidence that the long term exposure seems determinant rather than short term exposure to pollution.

Table 2: Estimation for academic results and accidents (Six months and twelve months before taking test, Medellin, 2007 to 2017)

	Six Months			Twelve Months		
Buffer	Math	Spanish	English	Math	Spanish	English
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
200	-0.0007*	0.0001	-0.0002	-0.0005*	0.0001	-0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0002)
300	-0.0005*	-0.0001	-0.0001	-0.0003*	-0.0001	-0.0001
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
400	-0.0005**	-0.0002	-0.0001	-0.0002*	-0.0001	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
500	-0.0002	0.0000	0.0001	-0.0001	0.0000	0.0000
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
HS FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	228587	228587	228587	228587	228587	228587
N	376	376	376	376	376	376

Note: *** p<0.01 ** p<0.05 * p<0.1. Measure of accidents is proportion of days surpassing a long term average (10 years) of accidents. Columns 1-3 using six month average of accidents; Columns 4-6 using twelve months accident average. Errors clustered by high school. HS FE: High School Fixed Effects; Time FE: time Fixed Effects of date of presentation.

Next, we check how results change based on accidents involving bikes or injured-dead people. These sort of accidents prolong traffic jams since they usually mean longer police and emergency care times. Table **??** shows similar results to baseline estimates, where coefficients present negative effects in Math at the smaller buffers. However, these coefficients are both larger and more significant, being more than double the effect size in baseline and significant at 5%. For accidents with injured-dead people (Panel B, Table 3), estimates are significant at 500 meters and both periods while bike-related accidents have a negative effect on Spanish scores at 400 meters and twelve months. Although not statistically significant, coefficients on Spanish and English are also larger and consistently negative compared to baseline estimates. Overall, results with bike accidents resemble those of accidents with injuries, in agreement with our expectation, given that bikers are at higher risk of being injured in a car crash.

Table 3: Estimates for academic results and accidents, bikes and injured-death people (Six months and twelve months before taking test, Medellín, 2007 to 2017)

	Six Months			**Twelve Months**		
Buffer	**Math**	**Spanish**	**English**	**Math**	**Spanish**	**English**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	Panel A. Bike Accidents					
200	-0.0018*	-0.0005	-0.0007	-0.0013**	-0.0003	-0.0004
	(0.0009)	(0.0009)	(0.0009)	(0.0006)	(0.0006)	(0.0006)
300	-0.0012**	-0.0006	-0.0003	-0.0008**	-0.0004	-0.0002
	(0.0006)	(0.0005)	(0.0005)	(0.0003)	(0.0003)	(0.0003)
400	-0.0009**	-0.0005	0.0000	-0.0006**	-0.0003*	-0.0001
	(0.0004)	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0002)
500	-0.0005	-0.0002	0.0002	-0.0003*	-0.0002	0.0000
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0001)	(0.0001)
	Panel B. Injured-Death People Accidents					
200	-0.0018**	-0.0007	-0.0007	-0.0011**	-0.0002	-0.0003
	(0.0008)	(0.0007)	(0.0008)	(0.0005)	(0.0004)	(0.0004)
300	-0.0010**	-0.0003	-0.0001	-0.0007**	-0.0002	-0.0002
	(0.0005)	(0.0004)	(0.0004)	(0.0003)	(0.0002)	(0.0002)
400	-0.0009***	-0.0004	0.0000	-0.0005***	-0.0002	0.0000
	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
500	-0.0005*	-0.0001	0.0002	-0.0003*	-0.0001	0.0000
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
HS FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs	228587	228587	228587	228587	228587	228587
N	376	376	376	376	376	376

Note: *** p<0.01 ** p<0.05 * p<0.1. Measure of accidents is proportion of days surpassing a long term average (10 years) of accidents. Columns 1-3 using six month average of accidents; Columns 4-6 using twelve months accident average. Errors clustered by high school. HS FE: High School Fixed Effects; Time FE: time Fixed Effects of date of presentation.

Similar to baseline, coefficients are bigger in magnitude when buffers around high schools are smaller and periods are closer, meaning that the effect is bigger when accidents occur closer to high schools and to the presentation date. Also, the effect appears from one month average for accidents involving motorbikes and two when accident involves injured-death people (Columns 1 to 6, Parts A and B, Table 4, Appendix A.1).

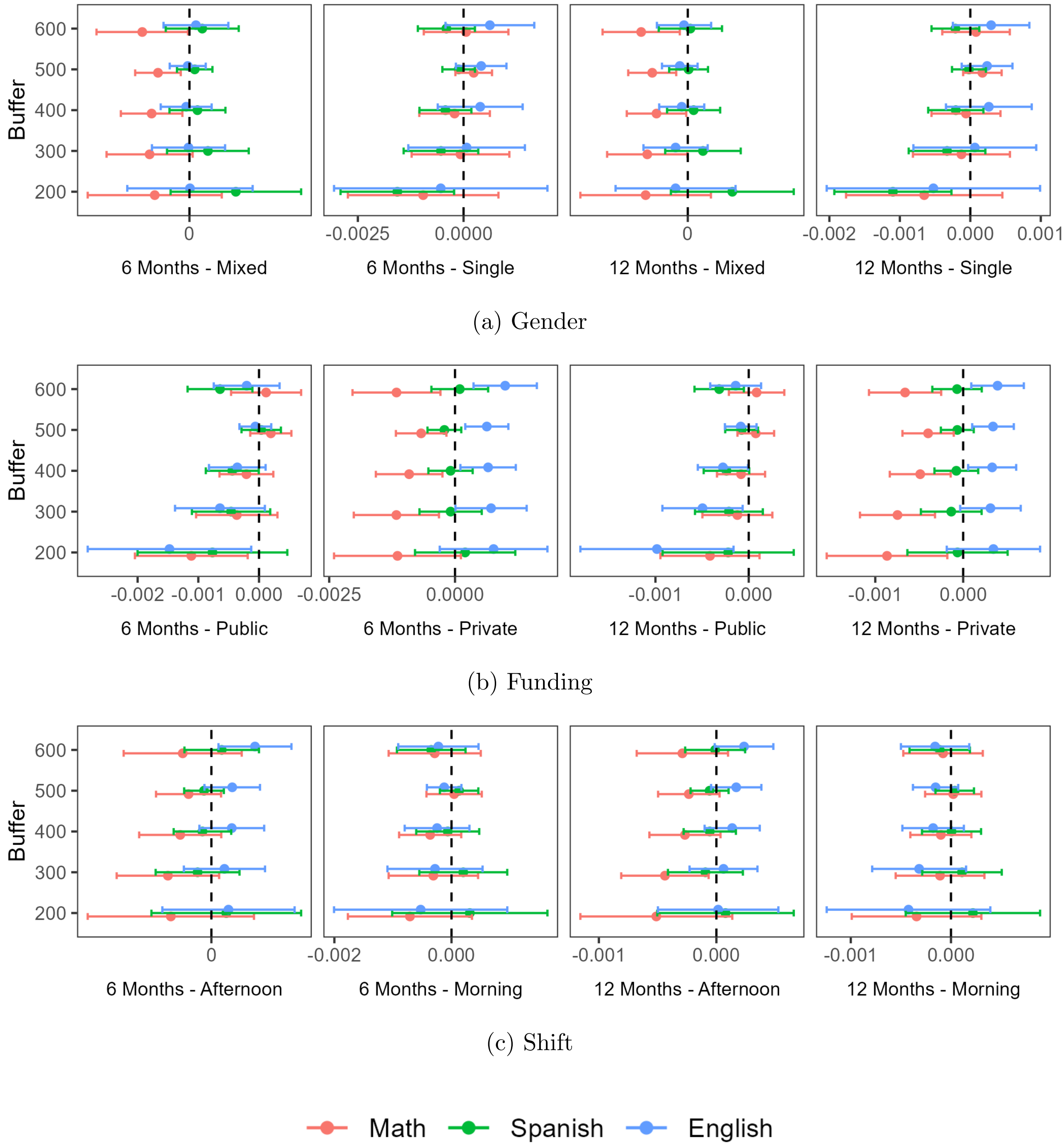
These results confirm that high accident rates are detrimental to academic performance.

Car accidents rise pollution emissions, in turn, deteriorating scores obtained by students (at high schools) taking the exit test Saber11 in Medellín. The effect is bigger when accidents happen closer to high schools, closer to exam dates, and involve motorbikes or injured people. Although these results are mostly on math, some negative significant effects on Spanish appears for accidents involving motorbikes and injured-dead people but it does not hold between periods (Columns 1 to 6, Parts and B, Table 5, Appendix A.1).

7.1 Heterogeneous Effects by School Group

To check for possible heterogeneous effects, we estimate equation 2 for different sub-samples of high schools such as public or private funding, mixed or single gender, morning or afternoon shift. Features of schools that could estimate differentiated results based on how each group share a particular feature within the city that could vary academic performance through high schools. We observe that there is a statistically significant effect of car accidents and performance on mathematics for sub-samples of mixed gender, private and afternoon high schools (only for the year average accidents). The effect ranges from -0.0005 SD (afternoon HS) up to -0.001 SD (private HS). While, performance on Spanish language seems to affected students at single gender high schools (only for 200 meters) and for students in public high schools (for 400 and 600 meters, graph b). The effect ranges from -0.0005 up to -0.001 standard deviations less than students in less polluted high schools. Finally, some results for English language show a positive effects which is unexpected. We highlight the difference among private and public schools, given that students at private schools on average are better off than those of public high schools (See Table 1). Pollution levels seem to affect more students at private high schools lowering the score in mathematics (and not for students at public high schools), while it lowers the score in English language for students at public high schools, who are commonly from lower socioeconomic strata or live in depraved areas which make them more prone to have worse academic results (due to socioeconomic disadvantages) that in turn are correlated to worse academic achievement. Our results exposed that those at the lower distribution of the score in English are the ones more affected by car accidents, while the effect on mathematics seems more relevant for those above the average score.

Figure 6: Estimation Results - High Schools Sub-samples



(a) Gender

(b) Funding

(c) Shift

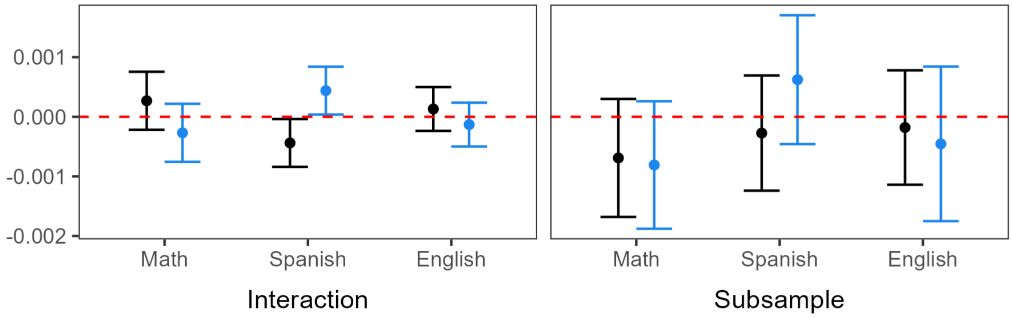
Note: Estimates including School and Time Fixed Effects and errors clustered by School. Observations and groups (a) Mixed Gender: 190574 and 341; Single gender: 38137 and 59 (b) Public: 151331 and 217; Private: 77380 and 162 (c) Morning: 113645 and 230; Afternoon: 115066 and 237.

7.2 Heterogeneous Effects by Student Gender

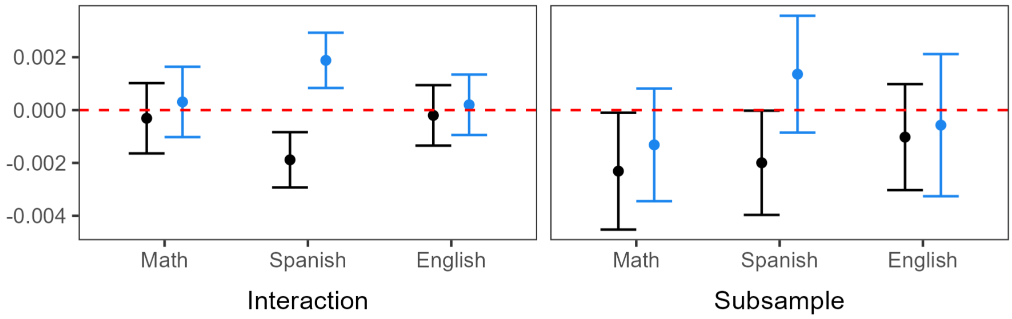
Now, we use student gender to differentiate estimates for males and females. We approach this in two ways, we estimate equation 2 for each subsample and alternatively, we interact the dummy variable gender with accidents. Figure 7 shows results for accidents 200 meters away from high schools and six months before exam date. While there is no statistically significant effects when we estimate for all accidents, we observe important differences with bikes and injuries related accidents, where female students register lower Spanish scores than their male counterparts.

This result disagrees with former studies that found men to be more vulnerable than women to air pollution. For example, Chen et al. (2017) found differentiated effects in verbal communication, arguing that pollution largely affects cognitive development by reducing white matter in the brain, and men have relatively less white matter than women. In a similar vein, Ebenstein et al. (2016) found lower test scores among men exposed to PM2.5 compared to women, possibly connected to the higher rates of asthma and ADHD rates in men. Nonetheless, Calderón-Garcidueñas et al. (2016) finds women to be disproportionately more affected than men to chronic exposure to PM2.5 and O3, showing that women performed worse on different cognitive abilities. Possible mechanisms proposed by the authors included sex differences in cognitive development, as well as complex interactions with weight and habits.

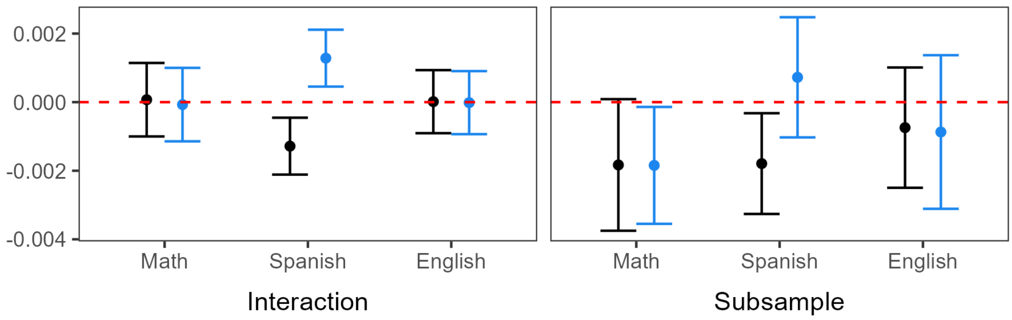
Figure 7: Heterogeneous Gender Effects by Accident



(a) Total



(b) Motorcycles



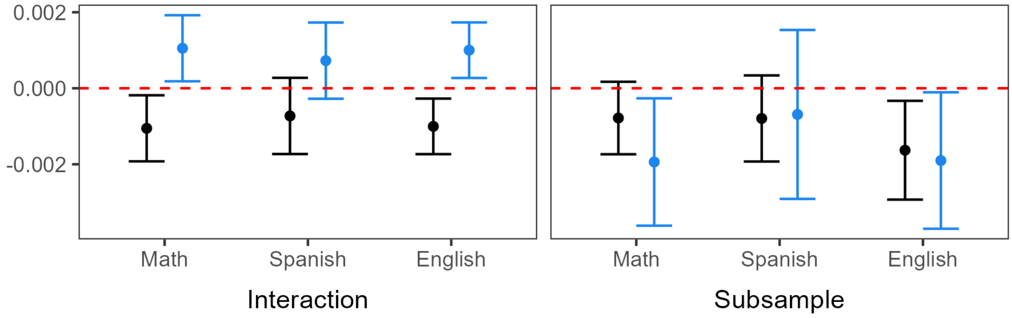
(c) Injured-Death

Note: Estimates including School and Time fixed effects and errors clustered by school. Accidents inside a 200 mts buffer and up to 6 months before test date. Observations in Subsample Male: 98123; Female: 130024.

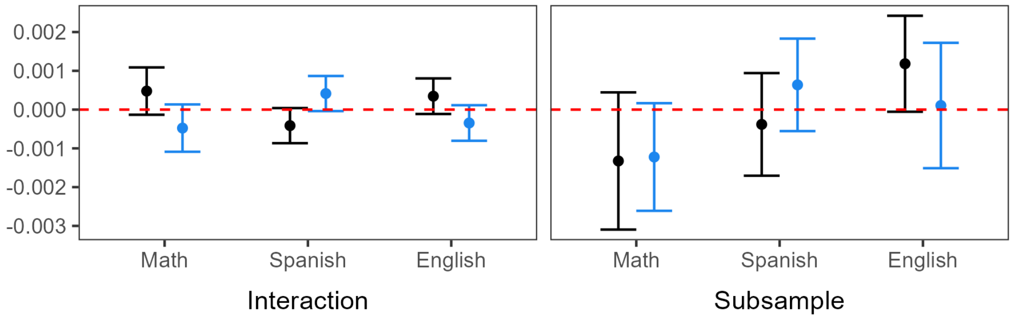
To shed some light on possible mechanisms, we further explore differences among men and women by estimating within schools sub-samples, to observe if female students are more affected by mobile air pollution than male students in all cases. Again, we estimate 2 with an interaction between gender and accidents and separately using only subsamples of males and females.

We observe that gender differences remain when students are from public schools but not from private schools. This gender gap in performance is seen in previously non significant results, in Math and English. While the mechanisms remain unclear, funding being correlated to families' income, better quality of education, etc., this result shows how better socioeconomic conditions could mitigate the gender disparities that come from biological differences, making one gender no more vulnerable than the other. We highlight Hollingsworth et al. (2020)'s work, where its shown how better nutrition gives children resilience to a highly polluted environment.

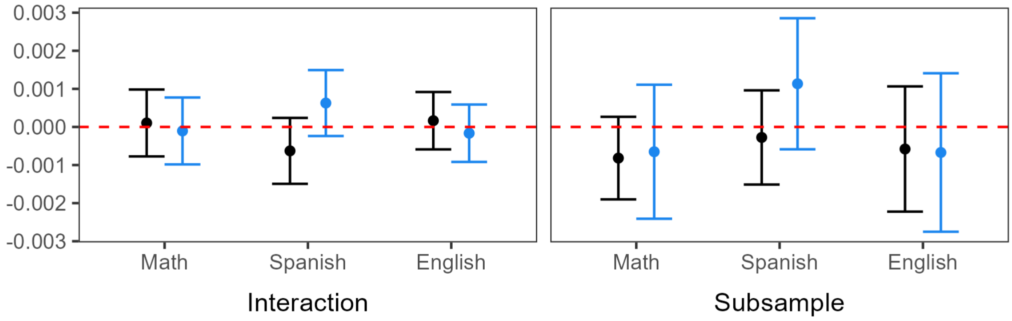
Figure 8: Heterogeneous Gender Effects by School Group



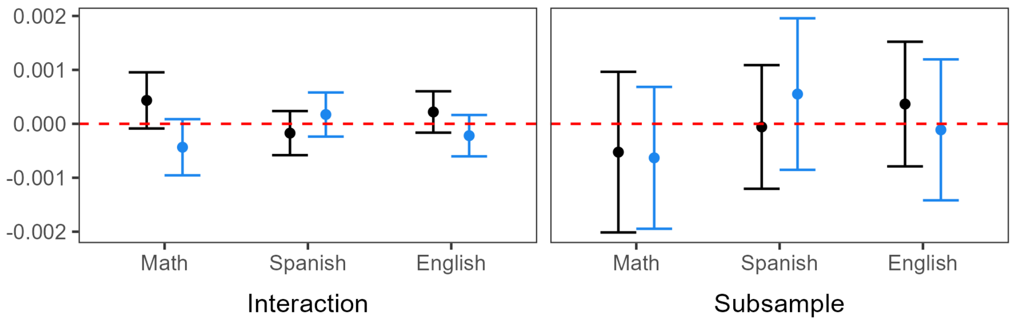
(a) Public Funding



(b) Private Funding



(c) Morning Shift



(d) Afternoon Shift

Note: Estimates including School and Time fixed effects and errors clustered by school. Accidents inside a 200 mts buffer and up to 6 months before test date.

8 Discussions and Conclusion

Exposing how air pollution endangers human health and cognitive development has been a subject hard to prove in developing countries due in part to limitations on pollution data. To overcome this, this paper proposes using car accidents as a good proxy, allowing us to shed light in how mobile air pollution is responsible for deteriorating academic achievement of students taking the exit test Saber11 in Medellín.

We find evidence that car accidents and mobile air pollution affect negatively academic performance of students. In particular, students in high schools near high levels of car accidents perform worse on average on Mathematics and English, specially when these accidents happen closer to schools, near exam dates and when they involve injuries. This result goes in accordance with previous evidence found in developed countries. For example, Sunyer et al. (2015) also find that students in high schools close to polluted roads perform worse that students in high schools away from polluted roads which influence cognitive development. Similar results are found by Kweon et al. (2018), where proximity to highways and industry is linked to reductions in proficiency on mathematics. Besides, our results are in accordance to Heissel et al. (2022) for students taking the (FCAT) in high schools near major roads in Florida.

On top of this, the results of this study highlight different effects depending on high school funding and student gender. On one hand, students at private schools are more affected in mathematics while students at public schools score worse in English, hinting at heterogeneous effects depending on where students sit in the score distribution. On the other hand, our results by gender show females to be more affected than males, specially in public schools.

Taking our results into account, several policy recommendations can be made. One set of policies are aimed at tackling the impact accidents have on air pollution. In this regard, recent legislation was passed, Law 2251 of 2022, promoted as a way to prevent accidents from affecting vehicle mobility, by prohibiting drivers to remain at the crash site when no people were injured. This policy, while helpful in some situations, could lead to a less than desired outcome. For example, according to local news, this law has come to the cost of a higher number of altercations between drivers, leading to physical confrontations [8]. Aside from the negative impact on the peaceful coexistence between members of society, these fights can in fact slow traffic, even more when severe injuries happen, defeating the main purpose of the initiative. We consider a better option to reform insurance law, requiring owners to obtain partial or full insurance on damages from accidents, promoting faster and more peaceful resolutions. A second, more optimal set of policies would be aimed at preventing car accidents from happening altogether, as well as reducing the rate injuries occur in car accidents. In this sense, reducing maximum speeds has proven effective at both, reducing accident rates and the severity of injuries when they occur. It's crucial to improve security for motorcycles, discouraging reckless driving, promoting road safety culture and enforcing rules about protective gear like helmets. Finally, a third set of policies can be aimed at making children and adolescents more resilient to the harmful effects of air pollution, for example, by improving children's diets in public schools.

We encourage further analysis of how mobile air pollution can be responsible for health and education outcomes on vulnerable populations. With car accidents as substitutes for air pollution in the city. Our exercise using vehicles accidents as measure of traffic can be use as a proxy mainly in big cities of developing countries, where similar regulatory and traffic issues are found.

[8] News from El Colombiano November 2022: "*A patadas y machetazos se están "arreglando" los choques solo latas en Medellín*" https://www.elcolombiano.com/antioquia/choques-sin-heridos-se-estan-arreglando-a-golpes-BI19441356.

References

Aizer, A., Currie, J., Simon, P., and Vivier, P. (2018). Do low levels of blood lead reduce children's future test scores? *American Economic Journal: Applied Economics*, 10(1):307–41.

Alexander, D. and Schwandt, H. (2019). The impact of car pollution on infant and child health: Evidence from emissions cheating.

Appatova, A., Ryan, P., LeMasters, G., and Grinshpun, S. (2008). Proximal exposure of public schools and students to major roadways: a nationwide us survey. *Journal of Environmental Planning and Management*, 51(5):631–646.

Benmarhnia, T., Bharadwaj, P., and Romero, M. (2015). Using instrumental variables for assessing the effects of air pollution on health: A cautionary tale.

Bharadwaj, P., Gibson, M., Graff-Zivin, J., and Neilson, C. (2017). Gray matters: Fetal pollution exposure and human capital formation. *Journal of the Association of Environmental and Resource Economists*, 4(2):505–542.

Bishop, K., Ketcham, J., and Kuminoff, N. (2018). Hazed and confused: The effect of air pollution on dementia. Technical report, National Bureau of Economic Research.

Black, S., Bütikofer, A., Devereux, P., and Salvanes, K. (2019). This is only a test? long-run and intergenerational impacts of prenatal exposure to radioactive fallout. *Review of Economics and Statistics*, 101(3):531–546.

Calderón-Garcidueñas, L., Reynoso-Robles, R., Vargas-Martínez, J., Gómez-Maqueo-Chew, A., Pérez-Guillé, B., Mukherjee, P. S., Torres-Jardón, R., Perry, G., and Gónzalez-Maciel, A. (2016). Prefrontal white matter pathology in air pollution exposed mexico city young urbanites and their potential impact on neurovascular unit dysfunction and the development of alzheimer's disease. *Environmental research*, 146:404–417.

Cebrián, A., Trillo, A., and González, A. (2019). *PISA 2018. Programa para la Evaluación Internacional de los Estudiantes. Informe español.* Ministerio de Educación y Formación Profesional.

Chang, J., Delfino, R., Gillen, D., Tjoa, T., Nickerson, B., and Cooper, D. (2009). Repeated respiratory hospital encounters among children with asthma and residential proximity to traffic. *Occupational and Environmental Medicine*, 66(2):90–98.

Chen, S., Oliva, P., and Zhang, P. (2018). Air pollution and mental health: evidence from china. Technical report, National Bureau of Economic Research.

Chen, X., Zhang, X., and Zhang, X. (2017). Smog in our brains: Gender differences in the impact of exposure to air pollution on cognitive performance.

CONPES (2018). Documento conpes 3943: Política para el mejoramiento de la calidad del aire. Technical report, Departamento Nacional de Planeación (DNP). Consejo Nacional de Política Económica Y Social.

Currie, J., Graff-Zivin, J., Mullins, J., and Neidell, M. (2014). What do we know about short-and long-term effects of early-life exposure to pollution? *Annual Review Resources Economics*, 6(1):217–247.

Currie, J. and Neidell, M. (2005). Air pollution and infant health: what can we learn from california's recent experience? *The Quarterly Journal of Economics*, 120(3):1003–1030.

Currie, J., Neidell, M., and Schmieder, J. (2009). Air pollution and infant health: Lessons from new jersey. *Journal of health economics*, 28(3):688–703.

Currie, J. and Walker, R. (2011). Traffic congestion and infant health: Evidence from e-zpass. *American Economic Journal: Applied Economics*, 3(1):65–90.

Deryugina, T., Heutel, G., Miller, N., Molitor, D., and Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, 109(12):4178–4219.

DNP, D. N. P. (2017). Los costos en la salud asociados a la degradación ambiental en colombia ascienden a $20.7 billones. Technical report.

Ebenstein, A., Lavy, V., and Roth, S. (2016). The long-run economic consequences of high-stakes examinations: Evidence from transitory variation in pollution. *American Economic Journal: Applied Economics*, 8(4):36–65.

Gehring, U., Tamburic, L., Sbihi, H., Davies, H., and Brauer, M. (2014). Impact of noise and air pollution on pregnancy outcomes. *Epidemiology*, pages 351–358.

Gillingham, K. and Huang, P. (2021). Air pollution, health, and racial disparities: Evidence from ports.

Graff-Zivin, J. and Neidell, M. (2013). Environment, health, and human capital. *Journal of Economic Literature*, 51(3):689–730.

Gupta, A. (2021). Jaha spotlight on air pollution and cardiovascular disease: A call for urgent action.

Halliday, T., Lynham, J., and De Paula, Á. (2019). Vog: Using volcanic eruptions to estimate the health costs of particulates. *The Economic Journal*, 129(620):1782–1816.

Heissel, J., Persico, C., and Simon, D. (2022). Does pollution drive achievement? the effect of traffic pollution on academic performance. *Journal of Human Resources*, 57(3):747–776.

Hollingsworth, A., Huang, M., Rudik, I., and Sanders, N. (2020). Lead exposure reduces academic performance: Intensity, duration, and nutrition matter. Technical report, National Bureau of Economic Research.

Knittel, C., Miller, D., and Sanders, N. (2016). Caution, drivers! children present: Traffic, pollution, and infant health. *Review of Economics and Statistics*, 98(2):350–366.

Kweon, B.-S., Mohai, P., Lee, S., and Sametshaw, A. M. (2018). Proximity of public schools to major highways and industrial facilities, and students' school performance and health hazards. *Environment and Planning B: Urban Analytics and City Science*, 45(2):312–329.

Lavy, V., Ebenstein, A., and Roth, S. (2014). The impact of short term exposure to ambient air pollution on cognitive performance and human capital formation. Technical report, National Bureau of Economic Research.

Meneses, R., Gonzalez-Gonzalez, M. V., Garay-Molina, N. M., Hoyos-Barba, M., and Agudelo-Henao, L. F. (2020). Informe de calidad de vida de medellín, 2016-2019. *Medellín, cómo vamos*, pages 1–318.

Nriagu, J. O. (2019). *Encyclopedia of Environmental Health*. Elsevier.

Ordoñez, P. J. (2020). Power plants, air pollution, and health in colombia.

Persico, C. and Venator, J. (2021). The effects of local industrial pollution on students and schools. *Journal of Human Resources*, 56(2):406–445.

Pons, M. (2022). The impact of air pollution on birthweight: evidence from grouped quantile regression. *Empirical economics*, 62(1):279–296.

Sánchez-González, S., Bedoya-Maya, F., and Calatayud, A. (2021). Understanding the effect of traffic congestion on accidents using big data. *Sustainability*, 13(13).

Sanders, N. (2012). What doesn't kill you makes you weaker: Prenatal pollution exposure and educational outcomes. *Journal of Human Resources*, 47(3):826–850.

Simeonova, E., Currie, J., Nilsson, P., and Walker, R. (2021). Congestion pricing, air pollution, and children's health. *Journal of Human Resources*, 56(4):971–996.

Slawsky, E., Ward-Caviness, C., Neas, L., Devlin, R., Cascio, W., Russell, A., Huang, R., Kraus, W., Hauser, E., Diaz-Sanchez, D., et al. (2021). Evaluation of pm2. 5 air pollution sources and cardiovascular health. *Environmental Epidemiology*, 5(3).

Sunyer, J., Esnaola, M., Alvarez-Pedrerol, M., Forns, J., Rivas, I., López-Vicente, M., Suades-González, E., Foraster, M., Garcia-Esteban, R., Basagaña, X., et al. (2015). Association between traffic-related air pollution in schools and cognitive development in primary school children: a prospective cohort study. *PLoS Medicine*, 12(3):e1001792.

Van-Vliet, P., Knape, M., De-Hartog, J., Janssen, N., Harssema, H., and Brunekreef, B. (1997). Motor vehicle exhaust and chronic respiratory symptoms in children living near freeways. *Environmental research*, 74(2):122–132.

Volk, H., Hertz-Picciotto, I., Delwiche, L., Lurmann, F., and McConnell, R. (2011). Residential proximity to freeways and autism in the charge study. *Environmental health perspectives*, 119(6):873–877.

Wang, S., Zhang, J., Zeng, X., Zeng, Y., Wang, S., and Chen, S. (2009). Association of traffic-related air pollution with children's neurobehavioral functions in quanzhou, china. *Environmental Health Perspectives*, 117(10):1612–1618.

WHO (2017). Evolution of who air quality guidelines: past, present and future.

World Bank, W. (2016). The cost of air pollution: strengthening the economic case for action.

Zweig, J., Ham, J., and Avol, E. (2009). Air pollution and academic performance: Evidence from california schools. *National Institute of Environmental Health Sciences*, 1:35.

A Appendix

A.1 Estimates equation 2 for other average periods of accidents. Short term and long term

Table 4: **Estimates relation of car accidents (200 to 500 meters around), and test results in mathematics, from one week to five months.**

	1 Week	1 Month	2 Months	3 Months	4 Months	5 Months
Buffer	(1)	(2)	(3)	(4)	(5)	(6)
A. All accidents	**Math**	**Math**	**Math**	**Math**	**Math**	**Math**
200	-0.0043	-0.0019	-0.0018*	-0.0017**	-0.0015**	-0.0009*
	(0.0035)	(0.0016)	(0.0010)	(0.0008)	(0.0006)	(0.0005)
300	-0.0021	-0.0011	-0.0011	-0.0012**	-0.0010**	-0.0007*
	(0.0026)	(0.0011)	(0.0007)	(0.0005)	(0.0004)	(0.0004)
400	-0.0030	-0.0011	-0.0011**	-0.0009**	-0.0007**	-0.0005**
	(0.0019)	(0.0009)	(0.0005)	(0.0004)	(0.0003)	(0.0002)
500	-0.0017	-0.0007	-0.0004	-0.0004	-0.0003	-0.0002
	(0.0023)	(0.0009)	(0.0006)	(0.0004)	(0.0003)	(0.0003)
B. Motorbikes						
200	-0.0059	-0.0049*	-0.0034*	-0.0028*	-0.0031**	-0.0023**
	(0.0051)	(0.0028)	(0.0018)	(0.0014)	(0.0013)	(0.0011)
300	-0.0083**	-0.0033*	-0.0022*	-0.0022**	-0.0018**	-0.0015**
	(0.0039)	(0.0018)	(0.0012)	(0.0010)	(0.0008)	(0.0007)
400	-0.0092***	-0.0029**	-0.0024***	-0.0017**	-0.0015**	-0.0012**
	(0.0030)	(0.0014)	(0.0009)	(0.0007)	(0.0006)	(0.0005)
500	-0.0051**	-0.0016	-0.0012	-0.0010*	-0.0008*	-0.0007*
	(0.0024)	(0.0011)	(0.0007)	(0.0006)	(0.0004)	(0.0004)
C. Injured-Death						
200	0.0022	-0.0037	-0.0046***	-0.0034***	-0.0031***	-0.0022**
	(0.0052)	(0.0023)	(0.0014)	(0.0012)	(0.0010)	(0.0009)
300	-0.0010	-0.0029**	-0.0027***	-0.0020***	-0.0017***	-0.0013**
	(0.0036)	(0.0014)	(0.0010)	(0.0008)	(0.0007)	(0.0006)
400	-0.0031	-0.0026**	-0.0024***	-0.0015***	-0.0013***	-0.0011***
	(0.0027)	(0.0011)	(0.0007)	(0.0005)	(0.0004)	(0.0004)
500	-0.0012	-0.0016*	-0.0013**	-0.0008*	-0.0007**	-0.0007**
	(0.0019)	(0.0009)	(0.0006)	(0.0005)	(0.0004)	(0.0003)

Note: *** p¡0.01 ** p¡0.05 * p¡0.1. Observations: 228587. High schools: 376. Estimates for equation 2 with errors clustered by high school. Each accident average is included alone in the estimation.

Table 5: **Estimates relation of car accidents (200 to 500 meters around), and test results in Spanish language, from one week to five months.**

	1 Week	1 Month	2 Months	3 Months	4 Months	5 Months
Buffer	(1)	(2)	(3)	(4)	(5)	(6)
A. All accidents	**Spanish**	**Spanish**	**Spanish**	**Spanish**	**Spanish**	**Spanish**
200	0.0023	0.0002	0.0003	-0.0002	-0.0002	0.0000
	(0.0029)	(0.0016)	(0.0011)	(0.0008)	(0.0006)	(0.0005)
300	0.0007	-0.0002	-0.0003	-0.0004	-0.0004	-0.0002
	(0.0024)	(0.0009)	(0.0006)	(0.0004)	(0.0003)	(0.0003)
400	-0.0009	-0.0003	-0.0004	-0.0004	-0.0003	-0.0002
	(0.0015)	(0.0006)	(0.0004)	(0.0003)	(0.0002)	(0.0002)
500	-0.0008	0.0000	-0.0001	-0.0002	-0.0001	-0.0001
	(0.0011)	(0.0004)	(0.0002)	(0.0002)	(0.0001)	(0.0001)
B. Motorbikes						
200	0.0043	-0.0021	-0.0010	-0.0008	-0.0009	-0.0006
	(0.0044)	(0.0026)	(0.0017)	(0.0014)	(0.0012)	(0.0011)
300	-0.0055	-0.0024	-0.0015	-0.0013	-0.0010	-0.0007
	(0.0039)	(0.0016)	(0.0012)	(0.0009)	(0.0007)	(0.0006)
400	-0.0065**	-0.0020	-0.0016**	-0.0009	-0.0007	-0.0006
	(0.0029)	(0.0012)	(0.0007)	(0.0006)	(0.0005)	(0.0004)
500	-0.0035	-0.0006	-0.0006	-0.0005	-0.0004	-0.0003
	(0.0021)	(0.0009)	(0.0005)	(0.0004)	(0.0003)	(0.0003)
C. Injured-Death						
200	0.0074**	-0.0015	-0.0026*	-0.0017	-0.0015*	-0.0010
	(0.0037)	(0.0022)	(0.0014)	(0.0012)	(0.0009)	(0.0009)
300	0.0021	-0.0010	-0.0014	-0.0009	-0.0007	-0.0005
	(0.0034)	(0.0014)	(0.0009)	(0.0007)	(0.0006)	(0.0005)
400	-0.0011	-0.0014	-0.0014***	-0.0007	-0.0006*	-0.0005
	(0.0024)	(0.0009)	(0.0006)	(0.0005)	(0.0004)	(0.0003)
500	0.0001	-0.0003	-0.0007	-0.0003	-0.0003	-0.0002
	(0.0019)	(0.0007)	(0.0004)	(0.0004)	(0.0003)	(0.0002)

Note: *** p¡0.01 ** p¡0.05 * p¡0.1. Observations: 228587. High schools: 376. Estimates for equation 2 with errors clustered by high school. Each accident average is included alone in the estimation.