Air Pollution and Road Safety

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Abstract

I link 6-hour air pollution exposure to the total number of car accidents in the city of Santiago by exploiting time-series variation from 2013 to 2016. In order to identify the causal effect of CO exposure, I use plausible exogenous variation in atmospheric stability to instrument CO exposure. I found a nonlinear relationship between CO exposure and the total number of car accidents. This result is driven by nonfatal accidents. Indeed, I do not find any impact on fatal accidents. In addition, the results hold under a battery of robustness checks. Although Santiago's CO level is far below the international criteria of a hazardous level, I argue that reducing the average level of pollution leads to a sizable increase in social welfare due to a reduction in the number of car accidents.

Key words: Air pollution, Car accidents, Instrumental variables.
JEL Codes: Q53, R41.

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Contents

1 Introduction

Over 1.2 million people worldwide die each year on roads, with millions more sustaining severe injuries and living with long-term adverse health consequences. Injuries produced by car accidents are estimated to be the ninth leading cause of death across all age group worldwide (WHO, 2015). Contrary to popular belief, the costs of car accidents are not only related to fatal injuries. The Insurance Research Council estimated that almost three-quarters of the costs of an accident are paid by actors that are not directly involved in the accidents, such as insurance companies, municipalities, police, and fire departments. Taking into consideration that car accidents represent between 1-2% of the GDP in middle-income countries (Jacobs et al., 2000), they impose an extremely high cost on society. Also, car accidents are reported to be a significant source of traffic congestion, causing considerable costs due to delays. Garrido (2012) estimates that the average cost of congestion in a small city as Antofagasta is higher than USD 1 million during a typical working day. Therefore, car accidents may represent a negative externality for the rest of society.

Given its relevance, previous work has focused on understanding the causes of car accidents. The main causes are divided in three: environmental, mechanical, and driver-related accidents (WHO, 2015). This paper seeks to provide new evidence on car accidents estimating the impact of contemporaneous exposure to air pollution on the total number of car accidents. Following an instrumental variable strategy, I estimate the exogenous changes in short run pollution exposure on the total number of car accidents. To do so, I constructed 6-hour window measures of pollution and car accidents for Santiago between 2013 and 2017.[1] Using this time-series database, I provide strong evidence that an exogenous increase in air pollution has a nonlinear positive effect on the total number of car accidents, increasing at a decreasing rate as exposure increases. The estimated economic benefit of decreasing the average level of CO in a 20% surpasses USD 1 million per year.

Using an OLS approach to estimate the effect of air pollution exposure on car accidents raises endogeneity concerns. Moreover, the pollution measures come from 10 stations distributed within the city so that a naïve OLS estimation may be severely biased downward. Instead, to identify the causal effect of air pollution on car accidents, I exploit the meteorological phenomenon of thermal inversions (measured as the degree of atmospheric stability) to instrument air pollution exposure. An inversion occurs when a mass of hot air gets caught above a mass of cold air, trapping pollutants in the troposphere. Although Santiago does not have a station that measure air temperature at different heights, I account for this using the difference in temperature of two stations that are located at different altitude.

Why would air pollution exposure affect car accidents? The medical, psychological, and biological literature have documented three potential ways relating air pollution and car accidents. First, air pollution exposure leads to physical symptoms, such as headaches, dizziness, and visual changes, that could increase the total number of car accidents. Second, it has been shown that air pollution affects exposed individual's psychologically, leading to mood changes. Levesque et al. (2011) show that rats exposed to higher levels of air pollution suffer from neuroinflammation, leading them to behave more aggressively. Aggresive behavior have been documented to increase car accidents. For example, Dingus et al. (2006) and Iversen and Rundmo (2002) show that aggressive driving substantially increases the probability of having a car accident. Finally, air pollution may impact the number of car accidents due to

[1] This understanding of car accidents considers all car crashes and pedestrians run over.

impaired reasoning. Consequently, an increase in air pollution may lead to an increase in car accidents. The background on the relationship between air pollution and car accidents is discussed in more detail in Section 2.

In order to show that the estimated effect is not spurious, I present several sensitivity checks that do not alter my conclusions. For example, the use of a nonlinear Poisson Count model to estimate the effect of air pollution provides qualitatively similar point estimates to my baseline IV results. Also, a distributed lag model finds no evidence for delayed impacts of air pollution. In addition, the results using aggregated level of pollution as treatment, instead of one pollutant, remain virtually unaltered, albeit the results are less robust. Finally, to explore if the results are driven by unobservable variables that covary with thermal inversions, I replace the treatment variable with pollution data from monitors across Chile. I do not find evidence that these unobserved variations are driving the results.

This paper contributes to the vast literature that studies the determinants of car accidents. Previous studies have shown that drunk driving is one of the major causes of car accidents, accounting for 19% to 26% of fatal accidents (WHO, 2015). Cotti and Walker (2010) find that the U.S. casino expansion, a place that is often associated with alcohol, leads to an increase in fatal car accidents induced by alcohol. Another well-known cause of road accidents is distracted driving. The use of mobile phones while driving is a major source of distraction and increases the risk of having an accident.[2,3] An overview elaborated by WHO (2015) suggests that drivers using their mobile phone when driving are four times more likely to be involved in an accident than those who not use them. Moreover, Faccio and McConnell (2017) found that the introduction of the virtual reality game Pokémon GO significantly increased the number of car accidents due to distracted driving, specially in the proximity of PokéStops.[4] My work contributes to this literature providing the first estimates regarding the impact of air pollution on car accidents in a developing country. To the best of my knowledge, only one work has documented the adverse effect of air pollution on car accidents. Specifically, Sager (2016) found an increase of 0.3 accidents per day for each additional 1 $\mu g/m^3$ in the daily concentration of NO_2 in the United Kingdom. Sager's estimated effect of air pollution is larger than the results of this paper. However, there is an important concern about the external validity of Sager's results to the developing context. If the dose-response function is concave in exposure level (as will be discussed in Section 2), marginal changes in pollution are less damaging at higher levels of air pollution. As a result, using Sager's estimates in a developing country would cause policymaker to overestimate the effect of air pollution on car accidents grossly.

Additionally, this paper analyzes a second order effect of the detrimental impact of air pollution on human health. Several articles have documented a negative impact of air pollution on health outcomes (Arceo et al., 2016; Chay and Greenstone, 2003; Currie and Neidell, 2005; Currie and Walker, 2011; Knittel et al., 2016; Schlenker and Walker, 2015). This impact on health manifests as distracted and aggressive driving and may lead to an increase in the total number of car accidents causing several types of injuries to drivers and pedestrians. Both symptoms have documented a large impact on nonfatal accidents. Therefore, one may expect a large impact of air pollution over nonfatal accidents, which are

[2] WHO (2015) shows that 69% of drivers in the U.S. had used their mobile phone while driving within the previous 30 days. In Europe, that percentage is ranged between 21% to 59%. This percentage is difficult to estimate in developing countries since data on mobile phone use is not routinely collected when accidents occur.

[3] WHO (2015) enumerate three ways of how distraction caused by using a mobile can affect driving performance. First, they affect the reaction time (especially braking time) of a driver. Second, it affects the ability to keep the vehicle in the correct line. Finally, the change in the driving patterns making drivers more unpredictable for other drivers.

[4] PokéStops are a well-identified location where Pokémon GO users can be found.

more affected due to distracted and aggressive driving (Young et al., 2007). As expected, I only find evidence that air pollution increases nonfatal accidents. Indeed, I find no effect on fatal accidents.

This paper also contributes to the emerging literature that relates air pollution to workers' productivity. In Chile, 7,5% of households have a head of household working as professional drivers (INE, 2014).[5] Although I cannot separate the effect over taxi and public transportation drivers, in my sample 33% of the accidents involve, at least, one professional driver.[6] This increase in the number of accidents due to exogenous changes in air pollution can be interpreted as a fall in productivity in the professional driver's sector. Hence, this paper relates to several economic papers that find a reduction in productivity due to an exogenous increase in air pollution (Chang et al., 2016a,b; Hanna and Oliva, 2015; Zivin and Neidell, 2012).

Furthermore, this work contributes to the regulatory debate about ambient quality standards. As well as Chang et al. (2016b); Currie et al. (2009); Schlenker and Walker (2015) and Zivin and Neidell (2012) show, my findings suggest that within-day variation in air pollution has a significant effect on car accidents bellow current EPA's mandates. I believe that this is particularly important because, in 2011, the EPA decided against lowering the existing CO standard due to insufficient evidence that low levels adversely affect human health. The maximum hourly CO concentration in the data is 20.6 ppm, which is below the ambient quality standard of 35ppm for any 1-hour reading. In other words, air quality levels were always within the limit. Yet, I find that fluctuations in pollution levels still have sizable consequences in car accidents.

The rest of the paper is organized as follows. Section 2 presents the medical and epidemiological background of air pollution and car accidents. Section 3 describes data. Section 4 presents the empirical strategy and the baseline results. Section 5 presents the instrumental variables results. Section 6 presents disaggregated effect and robustness checks. Finally, Section 7 concludes.

2 Air Pollution, Human Health and Car Accidents

This study focuses on carbon monoxide (CO) exposure. CO is a colorless, odorless gas that has been documented to have detrimental effects on humans. This paper documents the causal relationship between CO exposure and the total number of car accidents. I remain agnostic on the underlying mechanisms of this link. However, research in the fields of medicine, psychology, and biology have documented three potential ways as to how CO exposure can affect car accidents.

The first of these ways, and perhaps most straightforward link between CO exposure and car accidents, indicates that exposure to CO can manifest as medical symptoms such as headaches, dizziness, and visual changes (Ernst and Zibrak, 1998; Kampa and Castanas, 2008; Piantadosi, 2002), leading to discomforting driving. Petridou and Moustaki (2000) found a negative correlation between driver's comfort and the probability of being involved in a car accident, especially in nonfatal accidents.

A second documented way that explain this effect, is that CO exposure may lead to psychological changes that can manifest as aggressive behavior. Exposure to common air pollutants, including CO, leads to oxidative stress and the inflammation of the nerve tissues in the body and brain. This neu-

[5] Professional drivers count for taxi, ambulance, public transportation, and trucks drivers.

[6] I estimate this percentage since CONASET database keeps record of the license type. I consider professional drivers every driver using a license type A, which is the license type used to drive an ambulance, a taxi and public vehicles.

roinflammation is linked to aggressive behavior in humans (Levesque et al., 2011; Rammal et al., 2008; van Berlo et al., 2010). Also, CO poisoning leads to an increase in brain blood flow (WHO and Raub, 1999), effect that is related to adverse behavioral changes, such as aggressive reactions (Benignus et al., 1992). Dingus et al. (2006) and Iversen and Rundmo (2002) show that aggressive driving increases the probability of having a car accident. Consequently, one could expect that CO exposure leads to an increase in car accidents due to aggressive driving.

Finally, CO exposure may lead to a negative impact on the driver's ability to think correctly, increasing the number of car accidents. This is justified through the formation of carboxyhemoglobin, as CO binds to hemoglobin, reducing the cardiovascular system's capacity to carry oxygen. Amitai et al. (1998) ran a lab control experiment which randomly assigned different level of exposure of CO to 92 students from the Hebrew University of Jerusalem.[7] They tested the students for several neuro-psychological dimensions. The main results indicated that exposed students performed worse, even at low exposure, in learning, attention, concentration, and visual processing tests. These results relate to the findings of Ebenstein et al. (2016) and Lavy et al. (2014), whose papers documented that students exposed to higher levels of pollution had worse results in Israel's standardized tests.

Additionally, several articles have shown a nonlinear effect on the dose-response function as the exposure levels increase (Ezzati and Kammen, 2001; Pope et al., 2009, 2011). Ezzati and Kammen (2001) find that, as CO exposure increases, households exposed to low and medium levels present an increase in the number of weeks its members suffer from respiratory illness. However, they find that the marginal effect of CO exposure increases at a decreasing rate. Also, WHO and Raub (1999) show that marginal increases in exposure, at low levels, lead to changes in blood flow and impaired visibility. On the contrary, dose-response in extreme exposure levels seems to increase at increasing rates. The symptoms of severe CO exposure go from nausea and respiratory arrest to death (Goldstein, 2008). Extreme CO concentrations are not a serious issue to this study since, as I will discuss later, Santiago's CO level is low. If the nonlinear dose-response at low CO levels translates to the total number of car accidents, one may expect a nonlinear impact of CO exposure on car accidents.

Natural and anthropogenic sources are the principal emitters of CO. About half of the carbon monoxide is created on the Earth's surface, whereas the rest is produced in the atmosphere (WHO and Raub, 1999). In urban contexts, the percentage of CO produced by anthropogenic sources increases. Gallego et al. (2013) shows that mobile sources and light-duty vehicles are responsible for 97% of CO in Mexico City and 94% in Santiago.

In an effort to provide public health protection, the Environmental Protection Agency (EPA) sets an ambient quality standard for pollutants considered harmful to public health and environment. For CO, EPA sets two criteria: a one hour maximum level of 35 ppm per hour and an eight-hour maximum average of 9 ppm. These criteria were not exceeded during the sample used.[8] Therefore, EPA's standards suggest that the CO exposure of the average inhabitant of Santiago is not high.

[7] The total sample was divided in two: 45 exposed individuals and 47 controls. None of the students in the sample knew the group in which they belong.

[8] A typical concern is the pollution proxy used. Since I use a 6 hour mean over the median of the SINCA's monitors, CO peaks can be attenuated by low levels of CO in other monitors or if, after a peak of CO level, the CO level of the following hours decreases rapidly. The maximum one-hour observed CO level in Santiago is 20.6 ppm. This level, although higher than the maximum level of the proxy used (i.e., 3.63 ppm), is far below EPA's mandate. So, although the monitor's level can differ from Santiago's average level used, both levels are below EPA's threshold.

3 Data

I compiled data from air pollution measures, car accidents, traffic and weather conditions for Santiago from the years 2013-2016. Each data source is described in detail below.

3.1 Car Accidents

I have a panel of traffic accidents with their causes (59 types as listed in Appendix Table A.1 and A.2) from the years 2013 to 2016 for 43 municipalities of the Metropolitan Region.[9] This information was provided by the SIAT Office of Carabineros de Chile. This database includes information regarding the date (day and hour), the number of people injured and death, gender and age of the driver, and some information about location (municipality and geographic region) as well as climatic conditions. The total sample includes 100,948 accidents, 44,215 of which involve injuries whereas 1,308 involves fatal accidents. The data is particularly useful since it allows to differentiate accidents by their causes. I aggregated the data into the total number of accidents in a 6-hour window, as well as the number of accidents with at least one fatality and injured. Also, I aggregated the accidents without any injured in that period.

3.2 Air Pollution and Weather Controls

Air pollution data for the period 2013-2016 comes from the Sistema de Información de Calidad del Aire (SINCA), a network of monitoring stations operated by the Chilean Ministry of Environment, which consists of 10 stations placed throughout Santiago.[10] The instruments and quality control procedures of the Santiago monitoring network follow recommendations from the Environmental Protection Agency of the United States of America and are subject to public scrutiny and occasional external review panels (Osses et al., 2013).

CO data during the period of study is reported as a 1-hour average per monitor. Each monitor reports the average number of particles per million. I constructed an aggregate of Santiago's pollution by taking the one-hour median of pollution level of the ten monitors stations. Then, I computed a mean of exposure at a 6-hour block level by averaging the one-hour aggregate pollution. Temperature, humidity, wind speed and wind direction data come from the same network.[11] A similar procedure is followed to construct the mean 6-hour level of these controls. As pollution and weather controls may differ within the city, I restricted the analysis to municipalities that have a geographical centroid within 15 km from a monitoring station.[12] This criterion restricts the analysis to 43 municipalities. In Table A.3 I present the municipalities used in this work.

Precipitation information comes from the Dirección Meteorológica de Chile, an entity under the Dirección General de Aeronáutica Civil. This data come in a 6-hour total precipitation for the period. I use measurements from the Quinta Normal station since it was the station with the less missing

[9]To make the sample comparable, I only take into consideration accidents that occur in a municipality where its centroid's location is within 15 km distance from a monitor.

[10]This paper uses Carbon Monoxide (CO) as the pollutant of interest.

[11]Temperature is reported in Celsius degrees. Humidity is a measure of relative humidity. Wind direction is the angle of the wind, relative to the north. Finally, wind speed is measured as meters per second.

[12]Several articles restrict their sample to the observations near a monitor. Some of them are Schlenker and Walker (2015) and Currie and Neidell (2005).

information during the period of the sample.

3.3 Atmospheric Stability

To compute the proxy of atmospheric stability I used data from the Lo Prado and Quinta Normal stations. This proxy is the difference in temperature between the two stations, which are located at different altitudes. Both stations rely on the Dirección Meteorológica de Chile and use the same procedure to measure temperature. Whereas Quinta Normal station is located at 500 meters above the sea level, Lo Prado is located at 1,100 meters above the sea level. I followed a similar procedure to the one used in section 3.2 to compute the 6-hours window aggregated temperature average. After computing 6-hour averages, I estimated the indicator of atmospheric stability as the difference between these temperatures.

3.4 Traffic

The proxy of the number of cars for the years 2013-2016 comes from Santiago's three main urban concessionaires.[13] Departamento de Coordinación de Concesiones de Obras Públicas (DCCOP), an entity under the Chilean Ministry of Public Infrastructure, provides this information. The DCCOP reports traffic flow data by type of car, toll's location and hour. Data is aggregated to the total number of cars by the hour. Then, I computed the total number of cars during 6-hour block. I used this data as proxy of the total number of cars on the street since no reliable data of this variable is collected for Santiago (Paredes, 2016).

3.5 Descriptive Statistics

Table 1 shows a general description of the data. Panel (a) provides information on the number of car accidents during a 6-hour block period. The information is split between reports of total, minor, major, and fatal accidents.[14] The mean number of car accidents are 17.27, 9.7, 7.3, and 0.23 accidents per 6-hour window, respectively. Panel (b) provides information about the number of cars counted by tolls in urban highways and on the periods of vehicular restrictions. In the sample, 2% of the periods has vehicular restrictions. Panel (c) shows the main statistics of CO level and atmospheric stability.

[Insert Table 1 here]

Figure 1 panel (a) presents the evolution over time of car accidents. The graph was constructed using log variables and thus represents the percentage change over time. Although different categories have different mean level of accidents, each category level of car accident appears to be virtually constant over time. I also analyze, in Figure 2, the intra-day evolution of accidents. Consistent with the pattern of cars on the streets, accidents are less frequent at night. However, while night accidents make up only a 20% of the number of accidents during the afternoon (i.e., the 6-hour window from 12 pm to 6 pm), this relationship changes when analyzing fatal accidents. Nighttime fatal-accidents make up more than 85% of fatal accidents in the afternoon.

[13] A concessionaire oversees maintaining the highway for a specified period. Also, they earn the tolls revenues of the highway for the period. These concessionaires are Grupo Costanera SpA, Vespucio Norte Express, and Autopista Central.

[14] Minor accidents correspond to accidents without any injuries. Major accidents correspond to accidents with any injuries.

[Insert Figure 1 here]

CO level has a strong seasonality with a peak in winter months, as Figure 1 panel (b) shows. The mean level of CO is 0.56, whereas its distribution is concentrated below 0.7 ppm and its standard deviation represents 90% of the mean level. The within and between day variation of CO is almost the same in the same. However, in winter months (May-August) within day variation is higher than between day variation. For example, for June within day variation is 1.5 times higher than between day variation.

[Insert Figure 2 here]

Finally, panel (c) of Figure 1 shows the evolution of the proxy of vehicles flow during the period. The graph was constructed using log variables. In the sample vehicles flow has steadily grown over time. Besides, the proxy has a clear seasonal behavior, increasing in September-December months, whereas decreasing between January to March.

4 Empirical Strategy

Using a time-series database, I estimated the link between ground level air pollution and contemporaneous car accidents for the city of Santiago, Chile.

4.1 Basic Specification

The number of car accidents is a function of several factors, such as number of cars on the streets, visibility, as well as many other atmospheric variables including wind speed, wind direction, temperature, humidity, and precipitation (WHO, 2015). I identified a new factor by which atmospheric variables affect the number of car accidents: air pollution. To model the effects, I adopt the following linear model:

$$y_{th} = \beta_{11}CO_{th} + \beta_{12}W_{th} + \beta_{13}G(W_{th}) + \beta_{14}Flow_{th} + \beta_{15}VR_{th} + \sigma_h + \mu_t + \epsilon_{th} \tag{1}$$

where y_{th} represents the logarithm of the total number of accidents in a day t on a 6-hour window h.[15] I chose log accidents because this provides an easier way to interpret the effects of the air pollution in percentage terms. CO_{th} corresponds to the average observed CO level at time t and 6-hour window h.[16] The variable W_{th} is a set of weather controls in the day t and the 6-hour window h, including average wind speed, temperature, humidity, precipitation, wind direction and the interaction between wind direction and wind speed. To model this relationship formally, as in Schlenker and Walker (2015), I define wind direction by the cosine of the difference between the wind direction at each monitor, and the direction in which Santiago's centroid is located. The variable will be equal to 1 in the case that the angle in which the wind is blowing equals the direction in which the centroid is located, and the variable will be equal to zero when they are at a right angle (the difference is 90^{o}). Controlling for temperature, rainfall, humidity,

[15] I consider y = log(total accidents$_{th}$ + 1) as the dependent variable.

[16] Using 6-hour window allows me to differentiate between night, morning and evening peaks, and off-peak periods, something that larger hour windows does not allow me to. This is especially important due to car flow have significant variation between these periods, an issue that can affect the number of car accidents. Besides, using shorter windows can lead me to overestimate the effect of contemporaneous CO exposure, because of spikes in CO exposure make already "polluted" drivers have an accident one period earlier.

and wind speed and direction is essential since air pollution levels have a clear seasonal pattern and these controls may independently affect car accidents in several ways. Rainfall affects the probability of an accident, as well as visibility, car flow, and the average speed (Agarwal et al., 2005; Keay and Simmonds, 2005; Maze et al., 2006; Wang et al., 2017). Temperature has also been documented as a risk factor for car accidents, with higher temperatures increasing the probability of a crash (Basagaña et al., 2015; Leard and Roth, 2016). Humidity and wind speed can affect crashes by impacting on vehicle stability and road conditions. Also, controlling for wind direction and its interaction with wind speed allows me to control for how CO disperses within the city. G(W_{th}) is the fourth polynomial in mean rainfall and wind speed. I chose these controls because they reduce my data's mean squared error.[17] VR_{th} is an indicator that takes value one if in the day t and window h there was a vehicular restriction, while $Flow_{th}$ is a proxy of number of cars on the street based on the tolls of urban highways.[18] I also control for temporal variation in car accidents by including 6-hour window fixed effect (σ_h) and a day fixed effect (μ_t). Using 6-hour windows fixed effect allows me to control for this window's common characteristics. For example, since visibility is one of the leading determinants of car accidents, including σ_h in the specification will help me to control the intensity of light during the day. Also, this fixed effect helps me to control for car-seasonalities within a day, like school entry, rush-hour or drunk drivers. Day fixed effect allows me to control for within-day invariant characteristics. The parameter of interest is β_{11}, which tells us the effect of an increase in air pollution concentration on local car accidents. Increases in air pollution lead to greater exposure for drivers and, presumably by the background discussed before, an increase in car accidents. Hence, I would expect this coefficient to be positive.

Measuring the car driver's exposure to pollution is not straightforward. Since an automobile is in constant movement, the CO to which a driver will be exposed will depend on the length and duration of the trip, the traffic on the streets, local conditions, etc. This is a severe caveat for my analysis, since assigning pollution exposure to a driver will depend on variables unknown to the econometrician.[19] To overcome this problem, I focus my analysis on average observed CO level at a city level, using a time-series database that contains Santiago's average conditions for every variable.

During the period of study, SINCA's monitors collect information on two more pollutants level: particulate matter 2.5 and ozone. I acknowledge the detrimental effect of both pollutants on human health, but I use CO as treatment variable for several reasons. First, the way ozone affects human health is unlikely to affect car accidents. Second, CO within-day variation is larger than $PM_{2.5}$ within-day variation. Larger within-day variation allow me to better estimate the effect of within-day changes in CO exposure on car accidents. Intraday variation is a relevant aspect of estimating the short-term effect

[17] I follow González et al. (2017) approach to determine the weather polynomials: first, I randomly separated my database into two groups. Second, I ran OLS equation 1 using 256 different combinations of polynomials. Then I predict the number of car accidents for the other subsample using the coefficients found before and calculated the mean squared errors. For computational reasons, I only did this 35 times. I chose the fourth polynomial in wind speed and precipitation, which were the combination of controls that minimized the squared mean errors that were repeated the greatest number of times (13 over 35).

[18] In Santiago, vehicular restrictions are determined by the Unidad Operativa de Control de Transito (UOCT) for all motorized vehicles when the level of PM_{10} is higher than the criteria fixed by the law. The restricted cars depend on the last number of the license plate. The controls are in effect from 7:30 am to 9 pm (6-hour window 2, 3 and half of 4). Paredes (2016) finds that VR reduces 14% the CO in the air.

[19] In addition to the problem explained before, exposure to pollution levels is typically endogenous. Since pollution levels differs within the city, individuals may sort into areas with better air quality depending, in part, on their income (Chay and Greenstone, 2003).

of air pollution exposure on car accidents. Although there is increasing evidence of the detrimental impact of long-term exposure to air pollution on human health that can relate to car accidents, this is not the focus of the study. Third, CO is mainly emitted by mobile sources. Light-duty vehicles are responsible for the 90% of the emissions of CO, whereas only for the 20% of $PM_{2.5}$ (Gallego et al., 2013; Jorquera, 2002; Ministerio del Medio Ambiente de Chile, 2016; O'Ryan et al., 2000). Therefore, this paper focuses on estimating a new externality of car use. Despite the fact that regulators have focused on cars as an important source of air pollution, the effect of car pollution on car accidents has not been taken into consideration for public policies. Finally, I use CO due to a concern about the external validity of Sager's results. Arceo et al. (2016) find that the estimated elasticity between CO and infant mortality is larger in a developing country, like Mexico, than in the US context. On the contrary, the estimated elasticity of particulate matter is relatively similar. Consequently, if this relationship translates to the pathways that link air pollution and car accidents, Sager's results may not be externally valid for Santiago.

4.2 OLS Results

The baseline estimates for the effect of CO exposure on the total number of car accidents are presented in Table 2. Column 1 shows the correlation controlling for 6-hour window and day fixed effect. In columns 2 and 3, I show the predicted effect including weather and vehicular controls, respectively. Finally, in column 4 I show the estimates controlling for weather polynomials. Each column of this table reports three different levels of clustering for standard errors: only adjusted for heteroskedasticity, by day, and by week-year, reported in parentheses, curly brackets, and squared brackets, respectively. It also presents the estimated beta coefficient of CO exposure and the mean number of car accidents by period.

[Insert Table 2 here]

These results provide a first statistical test documenting a robust positive correlation between CO exposure and the total number of car accidents. It shows that the inclusion of linear and nonlinear weather controls increases the predicted effect of CO exposure. Also, the fit of the model also increases with the inclusion of these controls, albeit not significantly. By contrast, the addition of vehicular controls does not change the predicted effect.[20] The effect of CO exposure is, in all specifications, statistically significant at 99% of confidence for all clustering levels.[21] These results suggest that CO exposure significantly increases the number of car accidents. For example, a 10 percent increase in CO exposure raises the total number of car accidents between 1.4% (the case without nonlinear weather controls) and 1.9% (the case

[20] One could argue that vehicular restrictions and car flow proxy are an outcome of CO level, and thus constitute a case of bad controls. Bad controls can cause bias estimations (see Angrist and Pischke, 2008, pg. 64-68). Since vehicular restrictions are decreed due to a high level of pollution the day before, and this day-before level of air pollution is highly correlated with contemporaneous air pollution, controlling for VR can lead to problems in the interpretation of the point estimate. The same concern occurs for the proxy of car flow. Nonetheless, the estimates of Table 2 do not change with the inclusion of these controls (columns 2-3). Also, in Appendix Table C.1 I estimate the preferred specification including these controls separately. The point estimates and the fit of the model remain virtually unaltered. Hence, none of the results in this paper are driven by the inclusion of vehicular controls.

[21] For the preferred specification (i.e., column 4), standard errors clustered at week-year tend to be larger than the other two. This pattern holds for all the specifications presented in the paper. Correspondingly, I chose this cluster when conducting inference, as they tend to be the most conservative approach to avoid over-rejection of the null hypothesis concerning the statistical significance of the coefficient of interest. Unless otherwise specified, I report standard errors and statistics of the hypothesis test that are robust to within-week correlation in the error term.

with nonlinear weather controls). Another way of interpreting the magnitude of the estimated effect is to analyze the beta coefficients. Beta coefficients show how an increase in one standard deviation of the independent variable (i.e., CO exposure) affects the dependent variable (i.e., number of car accidents) regarding its own standard deviation. The point estimates of columns 2-4 suggest that an increase in CO exposure by one standard deviation leads to an increase between 0.17 and 0.22 in standard deviation of the number of car accidents. Both methods (i.e., the point estimates and the beta coefficients) suggests a consistent increase in the number of car accidents due to increases in CO exposure.

One concern about the point estimates reported in Table 2 is that the results are driven by outliers in CO level and are not representative of the regular CO exposure. Although CO level is far below international criteria in all observations of the sample, I address this issue in Appendix Table C.2. In column 1, I estimate Equation 1 using a logarithm transformation of CO exposure, whereas in column 2 I present the point estimate using winsorize at 5% pollution data.[22] Both corrections take into consideration outliers: the first one uses a concave transformation of CO level; thus, pollution increases at a decreasing rate. The second one replaces the lowest and highest 2.5 percentiles with the value of the 2.5 and 97.5 percentiles, respectively. Both results are consistent with the point estimate found in this section, albeit the beta-coefficients are slightly larger in the estimations of Appendix Table C.2.

These baseline estimates presented above came from a model in which CO exposure is taken as an exogenous variable. In the following section, I relax this assumption and use an instrumental variables approach. This approach corrects three possible threats to the interpretation of the point estimates presented in this section: omitted variables, measurement error in the exposure level of CO, and reverse causality.

5 IV approach

In the absence of a source of exogenous variation on pollution, it is difficult to interpret the previous results as causal. Although I attempt to account for several confounding factors, there are three potential problems with the OLS strategy. First, there may exist omitted transitory determinants of car accidents that may also covary with pollution and are not considered in the specification. If such omitted variables exist, the least squares estimate of the coefficient on CO exposure (e.g., β_{11}) will be biased. This could occur, for example, if weather seasonality within a 6-hour window, like morning fog, affects car accidents. These omitted variables lead to biased estimates of the effect of CO exposure on car accidents.

A second potential concern is reverse causality. On the one hand, cars are the primary emitters of CO. For instance, in Santiago more than 90% of carbon monoxide is produced by light vehicles (Gallego et al., 2013; Jorquera, 2002; Ministerio del Medio Ambiente de Chile, 2016; O'Ryan et al., 2000). On the other hand, air pollution can affect the number of cars on the street through vehicular restrictions. In Santiago, if the level of air pollution exceeds certain level decreed by law, 20% of the fleet is banned from going out on the streets. Also, people may sort and choose not to drive, to protect the environment, when the pollution level is high. Moreover, susceptible people, such as asthmatic or older adults, may prefer not to drive in polluted days due to health reasons.

In addition to omitted transitory determinants and reverse causality, measurement error is a third

[22] Figure 3 presents the 2.5 and 97.5 percentiles as dashed lines.

concern for an OLS specification. I proxy driver exposure to CO as a 6-hour average of medians across stations in Santiago. This methodology raises two concerns about the level of exposure. On the one hand, as I take an average of the levels reported by Santiago's monitors, this average level may not be representative of the city's general air pollution level. Osses et al. (2013) find that two monitors - Parque O'Higgins and Independencia - are centrally located and representative of general pollution patterns in metropolitan Santiago. The correlation between the CO proxy used and the level of these two stations is high, over 0.9 (see Appendix Table A.4 for specifics). On the other hand, I only have the monitors level of pollution, so the real exposure of driver's exposure may differ from the station's measurement. Several articles have documented that the pollution measurement of fixed monitors differs from measurements from personal monitors attached to individuals in urban settings (Chang et al., 2000; O'Neill et al., 2003). Measurement error may underestimate the effect of pollution on car accidents.

To address these potential sources of bias, I need an exogenous source of variation on pollution to use an instrumental variable approach. This strategy would correct not only for the reverse causality and omitted variable biases but also for the differential measurement error in the endogenous variable if the measurement error has a classical form (e.g., Wooldridge, 2002, ch. 5).[23] I use atmospheric stability as an instrument for local air pollution in the following first stage regression equation:

$$CO_{th} = \alpha_{11}AS_{th} + \alpha_{12}W_{th} + \alpha_{13}G(W_{th}) + \alpha_{14}Flow_{th} + \alpha_{15}VR_{th} + \delta_h + \varphi_t + \psi_{th} \tag{2}$$

where AS_{th} is a continuous indicator of atmospheric stability in day t and 6-hour window h. I cluster standard errors at the week-year level. The cluster-robust variance-covariance estimator implicitly adjusts standard errors to adequately account for serial correlation in air pollution over the week. Controlling for temperature and rainfall is essential for the exclusion restriction to hold since inversions have a clear seasonal pattern and these variables may independently affect car accidents (Basagaña et al., 2015; Leard and Roth, 2016; Maze et al., 2006; Wang et al., 2017).[24] In the following subsection 5.1, I explain this instrument.

5.1 Atmospheric Stability as Source of Exogenous Variation in Pollution

I exploit the degree of atmospheric stability, measured as thermal inversions, as a source of exogenous variation in CO level. This phenomenon consists in a reversal of the temperature's normal behavior in the troposphere. While on most days, temperature decreases with altitude, inversion periods are characterized by increasing temperature as altitude increases. Thermal inversions result in high stability in the troposphere that does not allow the proper ventilation of pollution.

[Insert Figure 4 here]

An inversion is characterized by its strength, top/base height, and top/base temperatures (see Figure 4). The inversion strength is the difference between the temperature at the top and the base of the

[23] Instrumental variables attenuate measurement error bias when the error on the independent variable is classical. The classical form is when measurement error is not correlated with other covariates and with the error term of the regression of interest (i.e., cov(γ,ϵ)=0 and cov(γ, X)=0, where γ is the measurement error and X is the covariates of the regression). For more information about instrumental variables see Wooldridge (2002), ch. 5.

[24] As Arceo et al. (2016) notice, including humidity and wind speed, is also essential as it is possible that an inversion can lead to a thunderstorm if moisture is trapped in the inversion.

inversion. A more stable atmosphere is characterized by having larger inversion strength. The thickness of an inversion is the difference in altitude between the top and the base of the inversion. The mixing depth of an inversion is the height from the ground to the bottom of the inversion (Jacobson, 2002).

[Insert Figure 5 here]

Unfortunately, in Santiago there is no station that measures air temperature at different altitudes. Therefore, I use a proxy of inversion strength as an indicator of atmospheric stability. This proxy is the difference in temperature between Lo Prado and Quinta Normal stations. Lo Prado station is located on top of a hill, having an altitude of 1,100 meters above sea level. On the contrary, Quinta Normal station is located at ground level, having an altitude of 500 meters above sea level. Both stations use the same methodology to measure temperature. This proxy gives a continuous instrument of atmospheric stability.

[Insert Figure 6 here]

Because Santiago is located within a valley, it is prone to suffer from thermal inversions. Most of the inversions occur in the winter months (May-August). However, they also occur in months with relatively high temperature (December-February). Thermal inversion does not represent a driving risk in itself, but it may result in a temporary accumulation of air pollutants. The combination of thermal inversions and Santiago's geographical topography cause that emissions get trapped in the troposphere (see Figures 5), causing higher levels of air pollution (Garreaud and Rutllant, 2006; Gramsch et al., 2006; Jacobson, 2002; Merino, 2006; Ministerio del Medio Ambiente de Chile, 2016). As Figure 6 shows, there is a strong relationship between the proxy of atmospheric stability and CO level. Once the sun's heat raises the temperature in the atmosphere and the temperature between layers equates (i.e., a reversal of the thermal inversion), the "lid" effect of the inversion disappears leading to a fall in air pollution levels (Arceo et al., 2016).

5.2 IV Results

Initially, I show the first-stage results. Table 3 provides the estimates when pollution is instrumented using atmospheric stability (the results of estimating Equation 2). As atmospheric literature suggested, thermal inversion is a strong linear predictor of CO level. Column 1 presents the result controlling for day and 6-hour window fixed effect. The point estimate is positive and highly statistically significant. This result suggests that one standard deviation increase in atmospheric stability predicts almost a 16% of a standard deviation increase in CO level. Accounting for weather controls slightly increases the point estimate. Whereas the inclusion of vehicular controls does not change the point estimate. Finally, in column 4 I present the result of the preferred specification. The point estimate prevails positive and statistically significant, albeit a little bit larger than in previous specifications. In the preferred specification, an increase of one standard deviation predicts almost a quarter of a standard deviation increase in CO level. Although the point estimates remains quite stable for the four specifications, the fit of the model substantially increases in column 4. Therefore, including nonlinearities in temperature and wind speed increases the explanatory power of the model, measured as R-squared.

[Insert Table 3 here]

Table 4 presents IV estimate for the preferred specification from Table 2. The sign and effect of the estimate are following the effect documented by the medical literature. However, the point estimate is statistically insignificant. Therefore, after instrumenting observed CO exposure with plausible exogenous variation in atmospheric stability, I do not find evidence that CO exposure has an impact on the total number of car accidents. For example, the point estimate suggests -albeit highly statistically insignificant- that one standard deviation increase in CO exposure is associated with a small effect on total car accidents: an increase of 0.005 accidents per 6-hour window. Just for seek of comparison, the OLS point estimate is larger that the IV estimate.

[Insert Table 4 here]

The results from Table 4 suggests that, using instrumental variables to estimate Equation 1, there is no linear impact of CO exposure on the total number of car accidents. However, epidemiology literature has documented diminishing marginal damage of the dose-response function at medium-low levels of CO exposure. If this relationship translates to the ways in which air pollution and car accidents relate, one should expect a nonlinear relationship between CO exposure and the total number of car accidents. In the following subsection 5.3, I take into consideration this possibility.

5.3 Nonlinearities in the Pollution-Accident Relationship

Epidemiology literature had documented that the health dose-response function is nonlinear in the pollutant level (Ezzati and Kammen, 2001; Pope et al., 2009, 2011). To test if this nonlinearity in health translates to the relationship between air pollution and the total number of car accidents, I estimate the following model:

$$y_{th} = \beta_{21} CO_{th} + \beta_{22} CO_{th}^2 + \beta_{23} W_{th} + \beta_{24} G(W_{th}) + \beta_{25} Flow_{th} + \beta_{26} VR_{th} + \sigma_h + \mu_t + \epsilon_{th} \tag{3}$$

where CO_{th}^2 is the second moment of the observed CO exposure. Since epidemiological literature has documented that the marginal effect in dose-response function of CO is not linear, increasing at a decreasing rate at low exposure, I expect that β_{22} has a negative sign.

One problem that arises is that using IV to estimate Equation 3 is a well-known case of forbidden regression.[25] In order to give a causal interpretation of the results, I estimate β_{21} and β_{22} using a Control Function approach (Newey et al., 1999). This method relies on, at least, one instrument. Adding the estimated residuals of the first stage (i.e., $\widehat{\psi_{th}}$ of Equation 2) introduces exogenous variation that serves as the control function. By adding an appropriate control function, the endogenous explanatory variables, CO_{th} and CO_{th}^2 in this case, become appropriate exogenous in a second-stage estimating equation (Wooldridge, 2015). While including first-stage error purges the estimates of the various biases outlined in Section 5, the standard errors need to be corrected for the variation coming from the first-stage estimation. In order to account for the first-stage sampling error, I obtain standard errors from 1000 bootstrap draws. For more details about control function methods see Wooldridge (2002), ch. 18.

Table 5 presents the estimates on the effect of nonlinear pollution exposure on car accidents. Column 1 does not include a control function, whereas column 2 adds the estimated errors of the first-stage.

[25] A forbidden regression crops up when the econometrician applies 2SLS reasoning directly to nonlinear models. For more information see Angrist and Pischke (2008), pg. 190-192.

This table shows that including the control function, changes the point estimates of CO exposure. In column 2, both coefficients associated with CO are statistically significant at usual levels. Also, the error term (i.e., $\widehat{\psi_{th}}$) is statistically significant at the 1%, giving an informal test of endogeneity in the OLS approach.

[Insert Table 5 here]

Adding a second moment of CO exposure changes the model. I now analyze the fit of the nonlinear model. The root mean squared error of the nonlinear estimation is 0.374, value that is lower than the RMSE of the linear approach (0.448). Besides, the F-value of joint significance of the parameters is larger in the nonlinear model estimation. Furthermore, the same pattern occurs when I compare the R-squared of both models. Therefore, the nonlinear model seems to better fit the data.

[Insert Figure 7 here]

I now turn to the analysis of the predicted effect of nonlinear CO exposure. Figure 7 plots the predicted marginal effect. The effect is statistically different from zero, and increasing in observed CO exposure until a threshold exposure of 0.632 ppm. This estimated threshold corresponds to the 75th percentile of the CO distribution. After that level, the marginal effect is negative. However, in higher percentiles, the marginal effect is not precisely estimated. Also, and just for comparison, Appendix Figure B.1 plots the predicted marginal effect for OLS and CF approach. The predicted impact of CO is larger in CF approach for low levels of exposure. However, after the 70th percentile of CO distribution, the OLS predicted effect is larger than CF effect.

To summarize, exploiting a plausible exogenous variation in atmospheric stability I do not find any significant impact on car accidents due to linear CO exposure. By contrast, once accounting for nonlinearities in CO exposure, I find evidence of a positive impact of CO exposure on car accidents, even at low levels of CO exposure.

6 Exploring Channels and Robustness Check

6.1 Disaggregate Effect

In this section, I explore the heterogeneous effect of CO exposure on car accidents according to their severity. I construct three different categories of accidents, based on the impact of the accident on drivers and pedestrian affected.[26] The method of estimation is analogous to the one used in Subsection 5.2 and 5.3, but restricting the dependent variable to the (logarithm) number of minor, major, and fatal accidents, respectively. Medical literature has documented that CO exposure leads to physical symptoms, such as headaches and dizziness. Petridou and Moustaki (2000) find that physical discomfort has a larger impact on nonfatal accidents. Consequently, I expect that CO exposure has a larger effect on minor and major accidents than on fatal accidents.

Table 6 presents the results of the disaggregated effect that CO exposure has on the number of car accidents. Panel (a) shows the results for minor accidents, while panel (b) presents them for major

[26] I follow Otero and Rau (2017) classification. Minor accidents are accidents where no one results injured. Major accidents are accidents with injuries but no fatalities. Fatal accidents are accidents with, at least, one death.

accidents. Finally, panel (c) presents the point estimates using fatal accidents as the dependent variable. Columns (1) and (2) present the estimates for a linear model of CO exposure, while columns (3) and (4) present the estimates for the nonlinear effect of CO exposure. Odd columns present an OLS approach, whereas even columns report an IV and CF approach.

[Insert Table 6 here]

The results in panels (a) and (b) are similar to the estimates from Section 5. These panels report that, under linear specification, there is not a statistically significant impact of CO on the aggregated number of minor and major accidents (column (2)). Also, both point estimates are virtually the same. Just for comparison, the impact of air pollution on total car accidents - albeit highly insignificant- is slightly larger than the estimated effect on minor and major accidents. Nonlinear CO exposure is, as in the previous section, statistically significant in both panels (both estimations are jointly significant at the 1%). Appendix Figure B.2 plots the predicted marginal effect of CO exposure on car accidents by its severity. As in the linear model, the predicted effect on total accidents is larger than the predicted effect on nonfatal accidents. Both predicted effects follow the same pattern, albeit the impact on minor accidents is slightly larger. These results suggest that a 10% increase in CO exposure from the mean level leads to a 0.4% increase in minor accidents and 0,37% increase in major accidents.

The results in panel (c) are less robust than the results of previous panels. The estimated effect is not statistically significant at usual levels of confidence in linear and nonlinear models. For the IV approach, the sign of the point estimate reverses, but remains statistically insignificant. It is important to notice that the explanatory power of the model, measured as R-squared, decreases substantially. Therefore, even after instrumenting CO exposure with plausible exogenous variation in atmospheric stability, I do not find an effect on fatal accidents.

Considering the results if this section, I have evidence of a positive impact of CO exposure on minor and major accidents. By contrast, no effect is found on fatal accidents. These results are in line with the potential ways that relate CO exposure and car accidents, as discussed in Section 2.

6.2 Potential confounding sources of variation

A common challenge in studies linking health outcomes to pollution measures is that ambient air pollutants are highly correlated. During the period of study, SINCA's network has readings for three different pollutants that have been documented as hazardous to human health: ozone, particulate matter 2.5 ($PM_{2.5}$), and CO. Although ozone exposure is harmful to human health, the main way that this compound affects human health is through irritation in lung airways (EPA, 2006a; Folinsbee and Hazucha, 2000; Folinsbee and Horvath, 1986; Kampa and Castanas, 2008), a symptom that is unlikely to affect the total number of car accidents.

In relation with $PM_{2.5}$, it has been shown that this compound can penetrate deep into human lungs and can pass beyond, towards the circulatory system, to induce both respiratory and cardiovascular effects (Seaton et al., 1995). Also, $PM_{2.5}$ can cause more subtle effects such as changes in blood pressure, irritation in the ear, nose, throat, and lungs, mild headaches and changes in hormonal levels (Ghio et al., 2000; Li et al., 2017; Pope, 2000).[27] CO and $PM_{2.5}$ are both highly correlated, with a peak level during

[27]Blood pressure can have many effects on human health, going from cognitive changes to a higher risk of having a stroke

the winter months, as it is shown in Figure 8's panel (a). Moreover, panel (b) shows that even within-day variation is highly correlated between CO and $PM_{2.5}$. Nonetheless, Appendix Table C.3 suggests that the results using $PM_{2.5}$ as the pollutant of interest are qualitatively the same as the estimates found in Sections 4.2 and 5.

Unfortunately, I cannot empirically test the separate effect of CO and $PM_{2.5}$ exposure on the total number of car accidents. However, in Appendix Table C.4 I provide two different tests to show that the estimated aggregate effect of air pollution is virtually the same as the point estimate found in previous sections. Panel (a) presents the point estimates using a Principal Component Analysis as treatment variable, whereas panel (b) presents the estimates using a 6-hour average Air Quality Index as observed pollution exposure.[28,29] For both aggregated measures, PCA and AQI, the beta coefficients of the linear model remain virtually unaltered. However, as the results shown in Section 5, the point estimates are highly insignificant. I interpret these findings as evidence that the linear impact of CO exposure on car accidents does not differ from the aggregated effect of air pollution. By contrast, the nonlinear model is less conclusive. On the one hand, PCA's predicted marginal effect is comparable in magnitude and significance with previous findings. On the other hand, AQI estimation is not statistically significant. These results suggest that, although nonlinear CO exposure has a positive effect on the number of car accidents, the findings for aggregated levels of pollution are not conclusive.

6.3 Temporal displacement and dynamics

The baseline regression model examines only the contemporary effect of CO exposure on total accidents. Contemporaneous estimates may lead to overestimating the total effect of CO on the total number of car accidents if spikes in 6-hour CO exposure make already "polluted" drivers have an accident one period earlier. In other words, the contemporaneous model may overestimate the real effect associated with permanently higher pollution exposure. Conversely, the contemporaneous effect can be underestimated if the number of car accidents responds sluggishly to changes in air pollution. For instance, if CO exposure impacts health in a period larger than 6 hours, the contemporaneous effect may be underestimated. Therefore, by only looking at contemporaneous response of car accidents to present pollution shocks, the estimates may be neglecting important dynamic effects of pollution on car accidents. I use Schlenker and Walker (2015)'s approach to explore these possible dynamics by estimating the following distributed lag model, including four lags in the CO exposure:

$$y_{th} = \sum_{k=0}^{4} \beta_{1k}\widehat{CO}_{t(h-k)} + \beta_{15}W_{th} + \beta_{16}G(W_{th}) + \beta_{17}Flow_{th} + \beta_{18}VR_{th} + \sigma_h + \mu_t + \epsilon_{th} \tag{4}$$

where $\widehat{CO}_{th}$ is the instrumented CO exposure from previous sections.[30] Table 7 presents the results for Equation 4. I present individual coefficients as well as the cumulative effect (the sum of the five coefficients). Column 1 presents the OLS estimates of the lagged model, whereas column (2) shows the IV results.

(Collins et al., 1990).

[28]Principal Component Analysis is a statistical procedure that uses orthogonal transformation to convert a set of observations of possibly correlated variables, CO and $PM_{2.5}$ in this case, into a set of values of linearly uncorrelated variables.

[29]Air Quality Index (AQI) is an aggregate composite measure of pollution developed by the U.S. Environmental Protection Agency (EPA, 2006b). The AQI ranges from 0 to 500 to rank air quality based on its associated health risks. I estimate Santiago's AQI level using CO and $PM_{2.5}$ as pollutants, using the EPA's algorithm.

[30]Unfortunately, I cannot extend this approach to nonlinear effect in observed CO exposure.

[Insert Table 7 here]

The cumulative effect is statistically equal to the contemporaneous point estimate in the IV approach. Also, the cumulative effect is larger than the comparable result in Table 4, albeit not statistically significant. This increase in the predicted effect might be because drivers exposed to already high levels of pollution are more likely to be affected by contemporaneous CO levels. However, the exact dynamics are hard to determine empirically given the lack of significance of the individual coefficients.

6.4 Count Model

The baseline estimates consist of a linear model relating the total number of car accidents to changes in CO exposure. To account for the non-negative and discrete nature of car accidents data, Table 8 presents the estimates of a quasi-maximum likelihood, conditional Poisson IV estimator. The dependent variable is the total number of car accidents, which differs from the previous dependent variable since I do not use a logarithmic transformation. As I use a CF approach to address issues about measurement error, reverse causality, and omitted variables, I adjust standard errors using bootstrap sampling procedure. Analogous to previous sections, I find that the linear CO exposure does not have any statistical effect, whereas adding the second moment of observed CO exposure suggests that total car accidents are sensitive to pollution fluctuations.

[Insert Table 8 here]

The coefficients no longer give marginal impacts and are difficult to interpret. To compare the marginal impacts of pollution exposure and total car accidents, Appendix Table C.5 presents the predicted increase in car accidents from one standard deviation increase in CO exposure. Column (1) and (3) present the OLS approach, whereas columns (2) and (4) show the IV and CF approach, respectively. Impacts are evaluated in the sample mean for nonlinear models. The results from the Poisson model are larger for IV and CF approach. Both types of models suggest that CO exposure has a small and positive effect on car accidents. For example, under nonlinear CO exposure, one standard deviation leads to an increase of 0.26 accidents in the CF approach and 0.62 in the Poisson count model.

6.5 Placebo Test

A key identifying assumption for IV estimates is the exclusion condition. This assumption allows the use of atmospheric stability as valid exogenous variation in CO level. A potential threat to this assumption is that atmospheric stability may, somehow, covary with car accidents through reasons unrelated to CO exposure (e.g., if atmospheric stability follows the same trend that economic activity, the instrument would also covary with economic activity, a variable that also affects car accidents).

To investigate the validity of this assumption, I analyze the predicted effect of CO exposure replacing Santiago's CO level with the analogous series from 5 other Chilean cities. I choose these cities because (i) all of them are located over 100 km from Santiago, (ii) the CO data was available for, at least, 75% of the observations in the study period, and (iii) most of them are cities with high economic activity. Ministerio del Medio Ambiente de Chile (2016) shows that emission sources are relatively similar among regions and the intra-day peaks are very correlated. Consequently, if there exists an alternative pathway whereby atmospheric stability affects car accidents, the estimated effect for the placebo CO should be positive. Appendix Table C.6 presents the point estimates of the respective CO placebo series by city, under a nonlinear exposure model. The estimated point estimates are not significant for four out of five estimations. The predicted marginal effect of the "significant" estimate is not statistically different from zero. Also, Appendix Figure B.3 plots the marginal effect of the placebo estimates. As before, none of them are statistically different from zero.

6.6 Economic Cost

In this section, I monetize the economic benefit from a 20% reduction in the average CO level over the total number of major car accidents. In Chile, two studies document the monetary cost of car accidents. In both studies, the associated costs of a car accident includes direct treatment, incident investigation, and on-the-road externalities. On the one hand, Hojman et al. (2005) estimate the value of life and the costs of severe injuries on traffic accidents. Unfortunately, they do not report the value of other types of accidents. On the other hand, CITRA (1996) has valuations for all types of accidents, but their estimates are substantially understated compared to other international evidence (Hojman et al., 2005).[31] To obtain a more precise estimate for the value of minor accidents, I use the life value given by Hojman et al. (2005) but estimate the minor accident cost using CITRA (1996)'s minor injuries relative cost ratio.[32]

Using the predicted effect on car accidents under nonlinear CO exposure given in Table 6's panel (b), a 20% reduction, from the mean values, in the yearly CO average level leads to more than USD $1 million benefits in the costs of minor injuries.[33] I view this estimated benefit of reducing the average CO level as a lower bound for four reasons. First, I only take into consideration the cost of value life, not taking into consideration other costs that arise from car accidents, such as congestion. Car accidents are associated with an increase in traffic congestion. Basso and Silva (2014) and Nelson et al. (2007) find that urban transport policies can be very effective in improving people's welfare due to diminutions in transportation time. Consequently, congestion reduction is an economic benefit not measured in this analysis. Second, in order to give a conservative estimate, I consider all injuries as minor. This assumption considerably understates the economic benefits since CITRA (1996)'s ratios are larger for moderate and serious injuries. Also, I assume that there was only one victim per car. Third, I only count for reported car accidents - any accident that the drivers agree to not report to the police officers are not taken into consideration. Also, Gonzalez and Rizzi (2016) argues that CONASET's database does not follow up on the people affected by the car accidents, understating the number of fatalities and injuries. Finally, I only take into consideration accidents that occurred in a restricted number of municipalities. If a driver is exposed in the sample municipalities but has an accident outside them, it is not being

[31] This difference is, in part, explained since CITRA document use the human capital approach.

[32] CITRA document was elaborated to provide a reliable scale to compare safety programs. In this document, it was estimated that the ratio between the cost of deaths and serious, moderate, and minor injuries was 0.5, 0.13, and 0.03, respectively. I explicitly assume that the ratio between fatal accidents and nonfatal accidents for Hojman et al. (2005) and CITRA (1996) is similar for all injury types.

[33] I estimate that the total number of accidents with injuries is reduced by 79.4 accidents per year. To monetize this result, I use Otero and Rau (2017) approach and update the UF and exchange rate to current values. Specifically, $\underbrace{US\$300,000}_{\text{Value of life}} \times \underbrace{\frac{CLP\$600}{CLP\$653}}_{\text{Chilean exchange rate}} \times \underbrace{\frac{UF28,781}{UF17,318}}_{\text{Inflation rate between 2005 and 2017}} \times \underbrace{0.03}_{\text{Death to minor injuries ratio}} \times \underbrace{79.4}_{\text{Increase in car accidents}}$

considered in the estimation.

7 Conclusions

This paper adds to the vast economic literature that seeks to understand the determinants of car accidents. In particular, it contributes to understanding the role of environmental factors by rigorously looking at the empirical relationship between CO exposure and the total number of car accidents. Using a time-series database for Santiago city between 2013 and 2016, I found a strong correlation between contemporaneous air pollution and the total number of car accidents. This result is consistent with the documented ways that air pollution may affect car accidents.

To determine whether this relationship is causal, I pursued an instrumental variable strategy. I exploit the plausible exogenous variation in atmospheric stability to instrument CO exposure. The IV results suggest a positive nonlinear impact of CO exposure on car accidents for low percentiles of the CO distribution. After a threshold level corresponding to the 75th percentile, the marginal effects are less conclusive. This result suggests a sizable economic benefit of reducing the average CO level: a 20% decrease in the average CO level leads to more than USD 1 million increase in social welfare, driven by a reduction in accidents.

I then turn to the heterogeneous impact that air pollution has on accidents according to their severity. I found that the estimated effect is driven by nonfatal accidents. Indeed, I found no impact on fatal accidents. The results hold under a battery of robustness checks. I found no evidence of temporal displacement on the effect of air pollution. Also, I found that the results do not differ from using an aggregate level of pollution as treatment variable. However, this result is less robust than previous estimations. Finally, I falsify Santiago's CO average level, replacing it with pollution levels from cities across Chile. I found no impact in the falsification tests.

The detrimental effect of air pollution on car accidents has important policy implications. For instance, restrictions on car circulation may have unexpected benefits on the number of car accidents, since cars are the leading emitters of CO. Moreover, this result provides new evidence for regulators to revise current air pollution standards, since I found evidence of a harmful effect of CO at levels far below current criteria.

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Figures

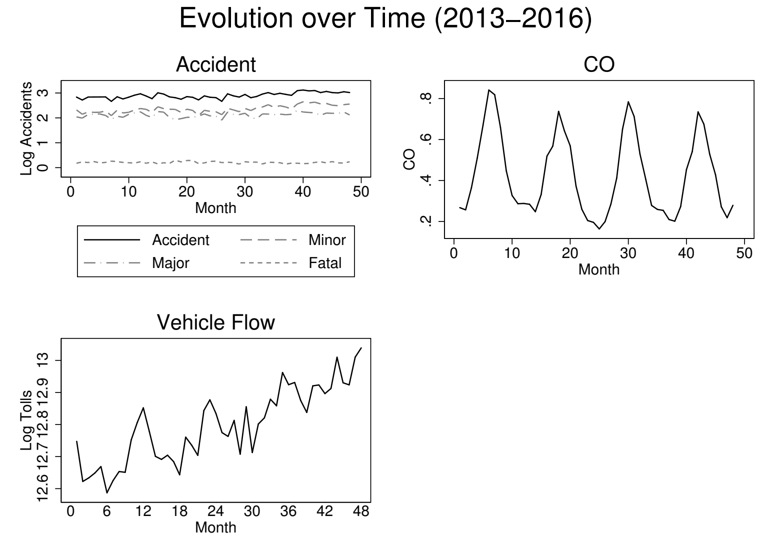

Figure 1: Evolution of accidents, vehicle flow and pollution over time (2013-2016)

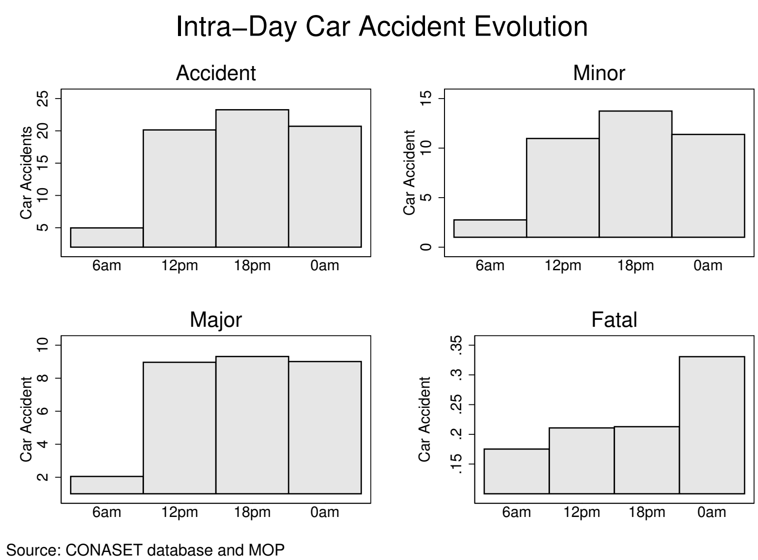

Figure 2: Evolution of car accidents over day (2013-2016)

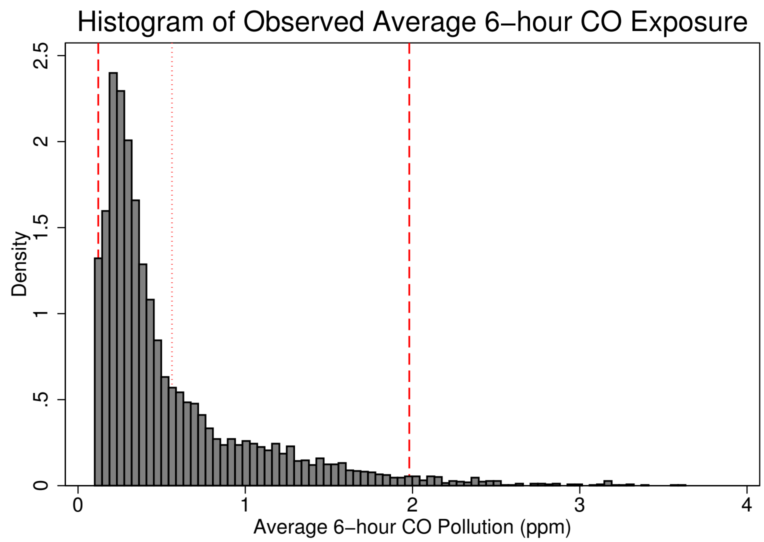

Figure 3: Observed distribution of CO.

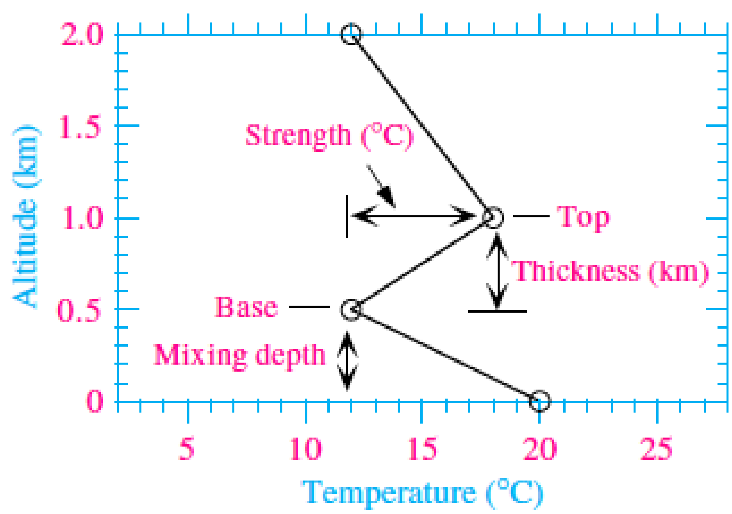

Figure 4: Thermal inversions characteristics. Figure comes from Jacobson (2002)

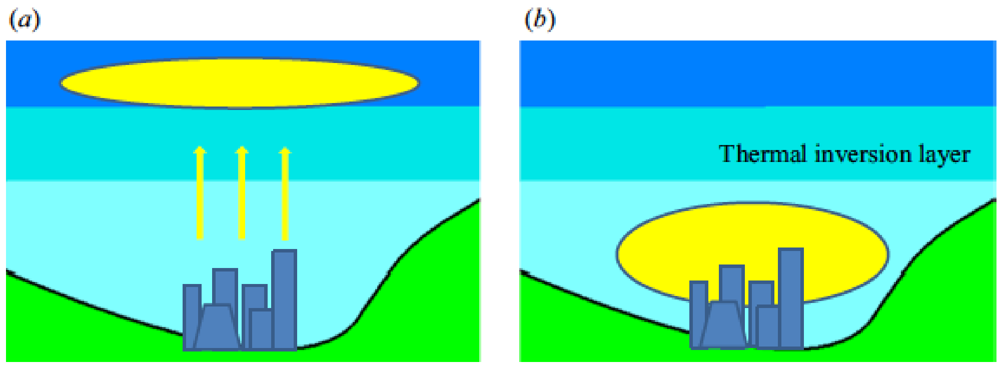

Figure 5: Thermal inversions. (a) Without Inversions, Pollutants Rise; (b) Pollutants are Trapped. Figure comes from Arceo et al. (2016)

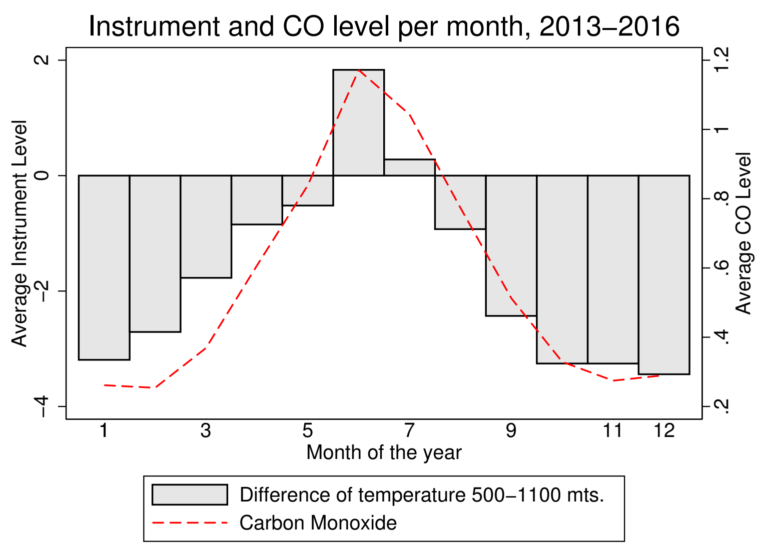

Figure 6: Average inversion strength, CO observed level, by month of the year.

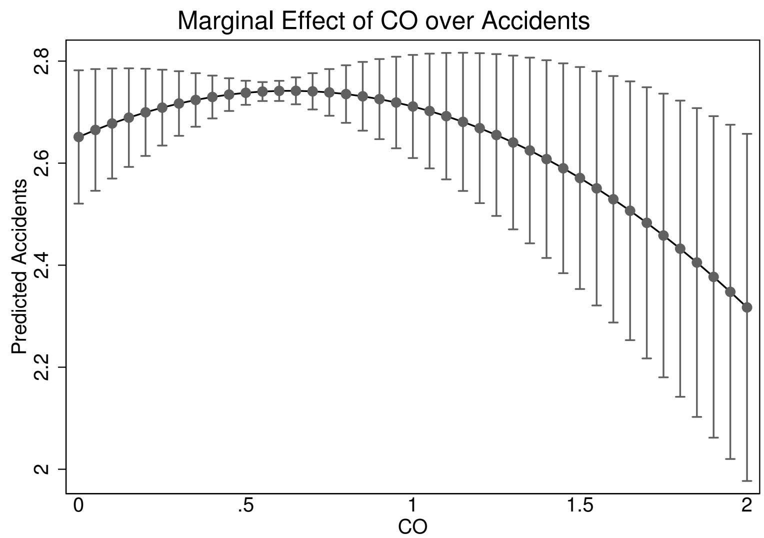

Figure 7: Marginal Effect of CO observed exposure over total car accidents.

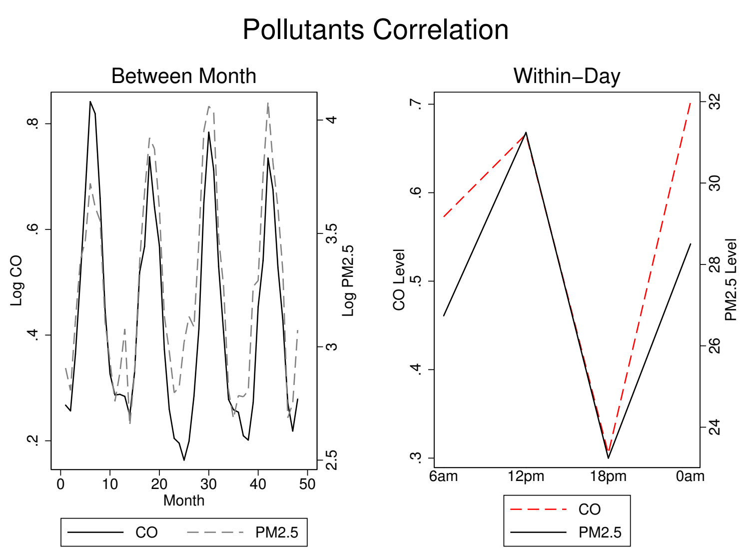

Figure 8: Between and within day correlation of CO and $PM_{2.5}$.

Tables

Table 1

Sample Statistics

	Mean	Standard deviation	Observations	Maximum	Minimum
	(1)	(2)	(3)	(4)	(5)
***Panel (a):* Car accidents**					
All	17.27	9.91	5,844	68	0
Minor Accidents	9.71	6.18	5,844	40	0
Major Accidents	7.33	4.67	5,844	28	0
Fatal Accidents	0.23	0.48	5,844	3	0
***Panel (b):* Highways toll**					
All types of cars	364,019.2	400,376.6	5,844	1,747,0324	61,911
Vehicular Restrictions	0.02	0.13	5,844	1	0
***Panel (c):* Pollution and Thermal Inversions**					
Median Carbon Monoxide 6-hour avg (CO)	.56	.50	5,844	3.63	.1
Stability	-1.69	4.43	5,777	15.12	-20.30

Note: This Table provides descriptive statistics for the key variables in the regression analysis. The unit of observation is a 6-hour window. Panel (a) provides information on car accidents, while panel (b) provides information on the number of cars circulating and vehicular restrictions. Panel (c) reports information on carbon monoxide and atmospheric stability. The sample has observations for four years, divided into 6-hour windows.

Table 2

OLS Estimates: Impact of Carbon Monoxide on Total Number of Car Accidents

	Dep. Var.:Ln(1+ Total Number of Car Accidents)			
	(1)	(2)	(3)	(4)
Carbon Monoxide	0.257***	0.266***	0.266***	0.345***
Robust s.e	(0.020)	(0.020)	(0.020)	(0.024)
s.e. clustered at day level	{0.020}	{0.020}	{0.020}	{0.024}
s.e. clustered at week level	[0.020]	[0.021]	[0.021]	[0.026]
Beta coefficient	0.165	0.170	0.170	0.221
Mean Number of Accidents	17.27	17.27	17.27	17.27
R-squared	0.728	0.729	0.729	0.734
N	5,844	5,627	5,627	5,627
6-hour window FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Weather Controls	No	Yes	Yes	Yes
Vehicular Controls	No	No	Yes	Yes
Weather Polynomial	No	No	No	Yes

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. Each coefficient corresponds to a separate regression. All the specifications include 6-hour window fixed effect and day fixed effect. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed. Vehicular Controls include a proxy of the number of cars on the streets and vehicular restrictions.

Table 3

IV Estimates: The Effect of Atmospheric Stability on CO (First Stage)

	Dep. Var.: 6-hour CO average			
	(1)	(2)	(3)	(4)
Atmospheric Stability	0.018***	0.021***	0.021***	0.025***
	(0.004)	(0.004)	(0.004)	(0.003)
Mean Level of CO	0.56	0.56	0.56	0.56
R-squared	0.259	0.280	0.280	0.417
N	5,844	5,627	5,627	5,627
6-hour window FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Weather Controls	No	Yes	Yes	Yes
Vehicular Controls	No	No	Yes	Yes
Weather Polynomial	No	No	No	Yes

Note: Robust standard errors clustered at the week-year level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a 6-hour window. Dependent Variable is 6-hour CO average. Each column corresponds to a separate regression. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed. Vehicular Controls include a proxy of the number of cars on the streets and vehicular restrictions.

Table 4

IV Estimates: CO and Number of Car Accidents

Dep. Var.	Ln(1+ Total Number of Car Accidents)
	(1)
CO	0.006
	(0.106)
Mean Number of Accidents	17.27
R-squared	0.723
N	5,564
F	410.51
F-Statistic	52.95

Note: Robust standard errors clustered at the week-year level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. The regression includes weather controls, weather polynomials, vehicular controls, 6-hour window fixed effect and day fixed effect. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed. Vehicular Controls include a proxy of the number of cars on the streets and vehicular restrictions.

Table 5

Impact of Non Linear CO on Total Number of Car Accidents

Dep. Var.	Ln(1+ Total Number of Car Accidents)	
	(1)	(2)
CO	0.875***	0.287***
	(0.072)	(0.110)
CO^2	-0.194***	-0.227***
	(0.022)	(0.022)
Mean Number of Accidents	17.27	17.27
R-squared	0.741	0.744
N	5,627	5,565
H_0: $\beta_{21} = \beta_{22} = 0$	282.02	106.00

Note: Standard errors are obtained from 1000 bootstrap draws. *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. Each column corresponds to a separate regression. Column (1) presents OLS point estimate, while Column (2) uses Control Function approach. All specifications include weather controls, weather polynomials, vehicular controls, 6-hour window fixed effect and day fixed effect. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed. Vehicular Controls include a proxy of the number of cars on the streets and vehicular restrictions.

Table 6

Disaggregated Effect of CO over Car Accidents

	(1)	(2)	(3)	(4)
Panel a: Minor Accidents				
	Dep. Var.:Ln(1+ Total Number of Minor Accidents)			
CO	0.311***	0.047	0.837***	0.319***
	(0.027)	(0.120)	(0.069)	(0.121)
CO^2			-0.193***	-0.220***
			(0.023)	(0.024)
Mean Number of Accidents	9.71	9.71	9.71	9.71
R-squared	0.687	0.679	0.692	0.694
N	5,627	5,564	5,627	5,565
Panel b: Major Accidents				
	Dep. Var.:Ln(1+ Total Number of Major Accidents)			
CO	0.309***	0.044	0.771***	0.288*
	(0.028)	(0.128)	(0.068)	(0.158)
CO^2			-0.169***	-0.197***
			(0.021)	(0.023)
Mean Number of Accidents	7.33	7.33	7.33	7.33
R-squared	0.663	0.650	0.668	0.669
N	5,627	5,565	5,627	5,565
Panel c: Fatal Accidents				
	Dep. Var.:Ln(1+ Total Number of Fatal Accidents)			
CO	0.042***	-0.175	0.069	-0.149
	(0.016)	(0.108)	(0.047)	(0.100)
CO^2			-0.010	-0.021
			(0.017)	(0.018)
Mean Number of Accidents	0.23	0.23	0.23	0.23
R-squared	0.029	0.027	0.029	0.030
N	5,627	5,565	5,627	5,565

Note: For columns (1) and (2) standard errors are clustered at week-year level. For columns (3) and (4) standard errors are obtained from 1000 bootstrap draws. *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a 6-hour window. Dependent Variable in panel (a), panel (b) and panel (c) is (log+1) total minor, major and fatal accidents, respectively. Odd columns present OLS estimates, whereas even columns present IV and CF approaches. Each coefficient corresponds to a separate regression. All the specifications include 6-hour window fixed effect and day fixed effect. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed. Vehicular Controls include a proxy of the number of cars on the streets and vehicular restrictions.

Table 7

Total Number of Car Accidents and Pollution - Lagged Pollution

	(1)	(2)
Pollution in t	0.350***	0.024
	(0.025)	(0.130)
Pollution in t-1	-0.098**	-0.004
	(0.041)	(0.060)
Pollution in t-2	-0.001	0.031
	(0.032)	(0.061)
Pollution in t-4	-0.018	-0.059
	(0.032)	0.057)
Pollution in t-4	-0.025	0.036
	(0.032)	(0.050)
Cum. Effect	0.208*	0.027
	(0.116)	(0.205)
R-squared	0.737	0.722
N	5,623	5,623

Note: Standard errors are obtained from 1000 bootstrap draws. *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. Each coefficient corresponds to a separate regression. This table replicates Tables 2 and 4 except that four lags of the pollution and instrumented pollution levels are included. Column (1) present OLS estimates, whereas Column (2) present IV estimates. Cumulative effect corresponds to the sum of all five coefficients. All the specifications include weather controls, vehicular controls and weather polynomials 6-hour window fixed effect and day fixed effect. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed. Vehicular Controls include a proxy of the number of cars on the streets and vehicular restrictions.

Table 8

Total Number of Car Accidents and CO - Count Model

	(1)	(2)	(3)	(4)
CO	0.182***	0.057	0.568***	0.248***
	(0.019)	(0.086)	(0.043)	(0.083)
CO^2			-0.136***	-0.156***
			(0.015)	(0.016)
N	5,626	5,564	5,626	5,564

Note: Standard errors are obtained from 1000 bootstrap draws. *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. Each coefficient corresponds to a separate regression. This table replicates Tables 2, 4 and 5 using a count model. Odd columns present OLS estimates whereas even columns present IV estimates. All the specifications include weather controls, vehicular controls and weather polynomials 6-hour window fixed effect and day fixed effect. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed. Vehicular Controls include a proxy of the number of cars on the streets and vehicular restrictions.

A Data

Table A.1

Types of Accidents

Cause: Panel A
Brakes
Steering
Electric
Suspension
Tires
Motor
Chasis
Overtaking without enough time and space
Overtaking without making corresponding signal
Forward by the berm
Forward surpassing continuous line
Overtaking on bends crossing, slope, tunnel, etc.
Driving under the influence of alcohol
Driving under influence of drugs or narcotics
Driving against the traffic direction
Driving while intoxicated
Driving poor physical conditions (fatigue, sleep or others)
Driving on the left axis of the road
Not attentive to driving traffic conditions
Driving without reasonable or prudent distance
Surprisingly change of way
No respect pedestrian passage
No respect vehicle passage
Passenger goes up or down while the vehicle is moving
Passenger traveling in the vehicle sill
Recklessness passenger
Drunk passenger
Pedestrian remains in the driveway
Pedestrian careless crossing
Recklessness pedestrian

Table A.2

Types of Accidents

Cause: Panel B
Drunk pedestrian
Pedestrian crosses pedestrians step out
Pedestrian crossing road or highway with no precautions
Traffic light not visible or maintained defectively
Disobey traffic red light
Disobey policeman indication
Disobey yield sign
Disobey stop sign
Disobey other signage
Traffic light in disrepair
Disobey traffic light flashing
Greater than the permitted speed
Not reasonable or prudent speed
Not reduce speed in intersection, road, etc
Excess of speed in restricted zones
Lower than minimum speed
Greater than the permitted load to vehicle
Load obstructs driver visual
Loads slips on driveaway
Load vehicle structure protrudes
Improper turning
Animals on the road
Backwards driving
Vehicle detention without signaling or deficient
Loss control of the vehicle
Suicide
Unidentified motives
Other causes
Escape by criminal act

Table A.3

Municipalities

Buin	Padre Hurtado	La Granja
Calera de Tango	Paine	San Joaquin Cerrillos
Penaflor	La Pintana	
Cerro Navia	Penalolen	San Miguel
Colina	Pedro Aguirre Cerda	La Reina
Conchali	Pirque	San Ramon
El Bosque	Providencia	Las Condes
El Monte	Pudahuel	Santiago
Estacion Central	Puente Alto	Lo Espejo
Huechuraba	Quilicura	Talagante
Independencia	Quinta Normal	Lo Prado
Isla de Maipo	Recoleta	Vitacura
La Cisterna	Renca	Macul
La Florida	San Bernardo	Nunoa
Maipu		

Table A.4

Correlation between computed average and representative monitor.

	Average CO 6-hour block	Average $PM_{2.5}$ 6-hour
	(1)	(2)
Parque O'higgins' monitor	0.9141	0.9252
Independencia's monitor	0.9315	0.9261

Notes: This Table presents the correlation between two representative station of Santiago's pollution (Osses et al., 2013) and the average used.

Table A.5

6-hour window

Hours in the block	Window ID
From 00:00 am to 06:00 am	1
From 06:00 am to 12:00 pm	2
From 12:00 pm to 06:00 pm	3
From 06:00 pm to 00:00 am	4

Notes: This Table presents the 6-hours window used in this work.

B Appendix Figures

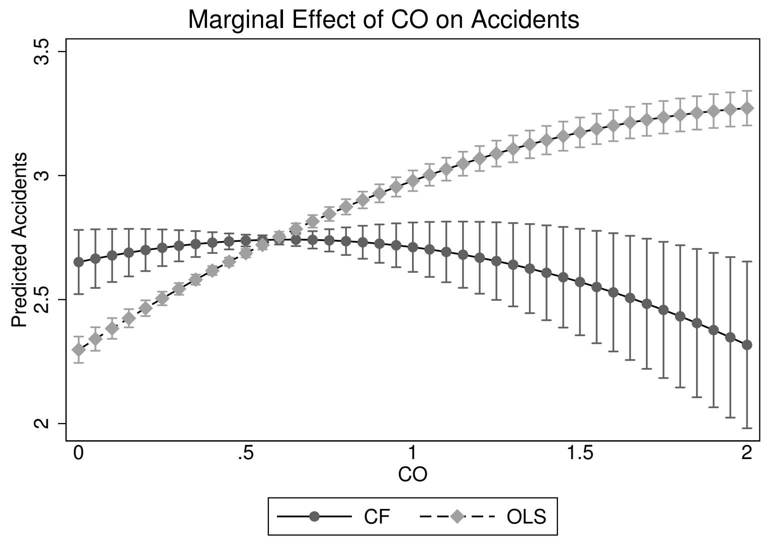

Figure B.1: Marginal Effect of CO observed exposure over total car accidents. OLS and CF approach.

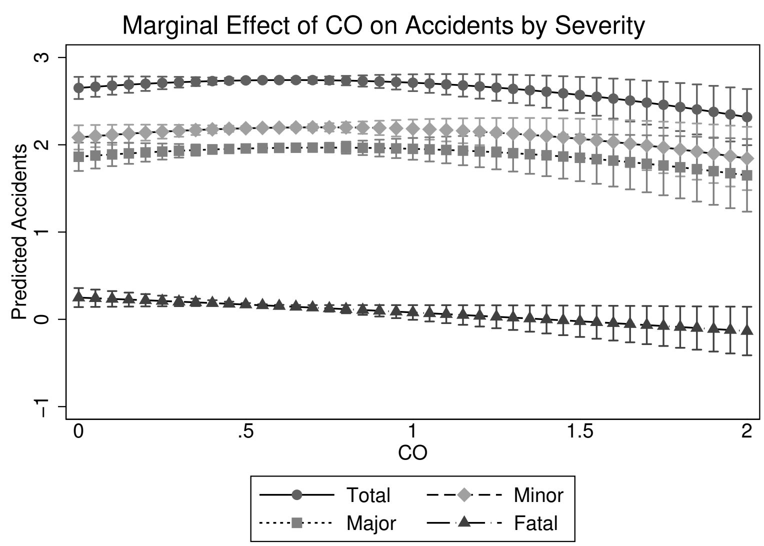

Figure B.2: Marginal Effect of CO observed exposure over accidents.

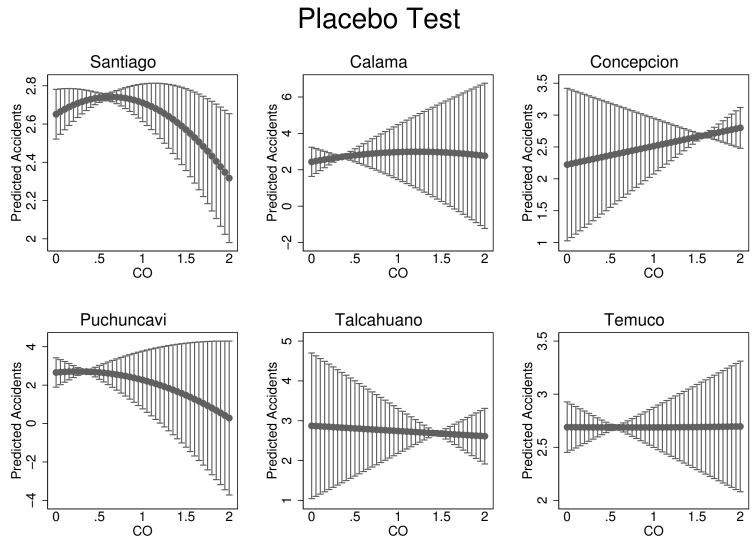

Figure B.3: Marginal Effect of CO observed exposure over accidents. Placebo Test.

C Appendix Tables

Table C.1

OLS Estimates: Impact of Carbon Monoxide on Total Number of Car Accidents

	Dep. Var.:Ln(1+ Total Number of Car Accidents)			
	(1)	(2)	(3)	(4)
CO	0.344***	0.345***	0.344***	0.345***
	(0.026)	(0.026)	(0.026)	(0.026)
6-hour window FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Proxy of Car on the Streets	No	Yes	No	Yes
Vehicular Restrictions	No	No	Yes	Yes
R-squared	0.735	0.736	0.735	0.736
N	5,627	5,627	5,627	5,627
F	441.98	426.47	430.59	416.12

Note: Robust standard errors clustered at week-year level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. Each coefficient corresponds to a separate regression. All the specifications include 6-hour window fixed effect and day fixed effect. Column (1) does not include any vehicular controls. Columns (2) and (3) add a proxy of cars on the streets and an indicator of vehicular restrictions, respectively. Column (4) include both vehicular controls. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed.

Table C.2

OLS Estimates: Impact of Carbon Monoxide on Total Number of Car Accidents

	Dep. Var.:Ln(1+ Total Number of Car Accidents)	
	(1)	(2)
Pollutant	0.834***	0.515***
	(0.054)	(0.032)
Beta Coefficient	0.284	0.277
R-squared	0.740	0.740
N	5,627	5,627
F	408.27	401.21

Note: Robust standard errors clustered at week-year level. *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. Each coefficient corresponds to a separate regression. All the specifications include 6-hour window fixed effect and day fixed effect. Column (1) shows the point estimates using log(co+1), whereas Column (2) shows the estimates of a censored distribution of CO. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed.

Table C.3

Impact of Particulate Matter 2.5 on Total Number of Car Accidents

	Dep. Var.:Ln(1+ Total Number of Car Accidents)			
	(1)	(2)	(3)	(4)
$PM_{2.5}$	0.007***	0.000	0.013***	0.005
	(0.001)	(0.003)	(0.002)	(0.003)
${PM_{2.5}}^2$			-0.000***	-0.000***
			(0.000)	(0.000)
R-squared	0.729	0.723	0.730	0.731
N	5,627	5,564	5,627	5,565

Note: Standard errors are obtained from 1000 bootstrap draws *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. Each coefficient corresponds to a separate regression. All the specifications include 6-hour window fixed effect and day fixed effect. Odd columns present an OLS approach, whereas even columns present IV estimates. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed.

Table C.4

Impact of Air Pollution on Total Number of Car Accidents

	Dep. Var.:Ln(1+ Total Number of Car Accidents)			
	(1)	(2)	(3)	(4)
Panel a: Principal Component Analysis				
Principal Component	0.125***	0.002	0.202***	0.029
	(0.010)	(0.039)	(0.017)	(0.044)
PC^2			-0.018***	-0.021***
			(0.003)	(0.003)
R-squared	0.734	0.723	0.736	0.738
N	5,627	5,564	5,627	5,565
Panel b: Air Quality Index				
AQI	0.004***	0.000	0.005***	0.001
	(0.000)	(0.002)	(0.001)	(0.002)
AQI^2			-0.000	-0.000
			(0.000)	(0.000)
R-squared	0.730	0.723	0.730	0.731
N	5,627	5,564	5,627	5,565

Note: Standard errors are obtained from 1000 bootstrap draws *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. Each coefficient corresponds to a separate regression. Panel (a) presents the estimates for PCA, whereas Panel (b) presents the estimates for aggregated AQI. All the specifications include 6-hour window fixed effect and day fixed effect. Odd columns present an OLS approach, whereas even columns present IV estimates. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed.

Table C.5

Impact of CO on Accidents

Panel a: Linear Model				
Total	2,97	0,05	1,57	0,49
Minor	1,5	0,23	0,79	0,26
Major	1,13	0,16	0,74	0,37
Fatal	0	-0,02	0,02	-0,12

Panel b: Non-Linear Model				
Total	5,64	0,26	3,57	0,62
Minor	2,99	0,34	1,94	0,34
Major	2,12	0,24	1,57	0,43
Fatal	0,01	-0,02	0,04	0

Note: This Table gives predicted *changes* in total number of car accidents. Panel (a) used Equation 1, while Panel (b) used Equation 3.

Table C.6

Placebo Tests

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Santiago	Calama	Concepción	Puchuncaví	Rancagua	Talcahuano	Temuco
CO	0.287***	0.907	0.292	0.405	-0.022	-0.130	-0.008
	(0.110)	(1.250)	(0.382)	(1.143)	(0.234)	(0.667)	(0.213)
CO^2	-0.227***	-0.371	-0.002	-0.795***	-0.033***	-0.000	0.005
	(0.022)	(0.277)	(0.002)	(0.257)	(0.007)	(0.002)	(0.007)
R-squared	0.744	0.730	0.720	0.722	0.729	0.723	0.726
N	5,565	5,142	4,388	5,511	5,295	5,519	5,226

Note: Standard errors are obtained from 1000 bootstrap draws *** p<0.01, ** p<0.05, * p<0.1. The unit of observation is a 6-hour window. Dependent Variable is the logarithm of the total number of car accidents. Each coefficient corresponds to a separate regression that uses the analogous series of CO level from 6 other Chilean cities. All the specifications include 6-hour window fixed effect and day fixed effect. Odd columns present an OLS approach, whereas even columns present IV estimates. Weather controls are 6-hour average humidity, temperature, rainfall, wind speed, wind direction and the interaction of wind direction and wind speed. It also includes a fourth polynomial in rainfall and wind speed.