I Z A Institute of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14599

On the Short-Term Impact of Pollution: The Effect of PM 2.5 on Emergency Room Visits

Evangelina Dardati
Ramiro de Elejalde
Eugenio Giolito

JULY 2021

DISCUSSION PAPER SERIES

IZA DP No. 14599

On the Short-Term Impact of Pollution: The Effect of PM 2.5 on Emergency Room Visits

Evangelina Dardati
CEP

Ramiro de Elejalde
Universidad Alberto Hurtado

Eugenio Giolito
Universidad Alberto Hurtado and IZA

JULY 2021

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

On the Short-Term Impact of Pollution: The Effect of PM 2.5 on Emergency Room Visits

In this paper, we study the effect of fine particulate matter (PM 2.5) exposure on Emergency Room (ER) visits in Chile. Our identification strategy exploits daily PM 2.5 variation within a hospital-month-year combination. Unlike previous papers, our data allow us to study the impact of high levels of pollution while controlling for avoidance behavior. We find that a one standard deviation increase in PM 2.5 increases respiratory ER visits by 1.4 percent. This effect is positive for all age groups but is stronger for children (less than five years old) and the elderly (more than 65 years old). Moreover, we find that the effects are stronger in geographical areas in which the share of emissions from residential wood burning is more than 75 percent. Finally, our results are robust to instrumenting pollution using wind direction and speed and to controlling for other pollutants.

JEL Classification: I12, I18, Q51, Q53

Keywords: air pollution, PM 2.5, emergency room visits

Corresponding author:
Eugenio P. Giolito
ILADES, Universidad Alberto Hurtado
Facultad de Economía y Negocios
Erasmo Escala 1835
Santiago
Chile

E-mail: egiolito@uahurtado.cl

1 Introduction

In recent decades, pollution has become a severe health hazard worldwide. An important source of air pollution, especially in urban areas, is fine particulate matter (PM 2.5). PM 2.5 are tiny particles with diameters smaller than 2.5 micrometers that, when inhaled, get deep into the lungs or into the bloodstream, causing a variety of health problems such as decreased lung function, aggravated asthma, irregular heartbeat, etc.[1] In fact, some recent studies find that PM 2.5 is associated with higher mortality for selected groups (Deryugina et al. (2019), Gong et al. (2019), Clay et al. (2021), Kloog et al. (2013)). In this paper, we study the causal effect of short-term daily variation in PM 2.5 on respiratory emergency room (ER) visits. We use data from Chile, a middle-income country with extremely high levels of air pollution, which, during most of the year, are well beyond what is considered safe.

The association between air pollution and health outcomes is well-documented in medicine and epidemiology (Anenberg et al. (2018), Peel et al. (2005), Szyszkowicz et al. (2018), Zanobetti and Schwartz (2006)). However, estimating the causal effect of pollution on health outcomes has many well-known challenges. First, individuals with different characteristics may sort into areas with different air quality. For example, higher-income individuals may spend more on health care or live in less polluted areas. Second, seasonal factors increase both pollution and the incidence of respiratory diseases. For example, because of the intensive use of heating, pollution is usually higher in winter, when there are also more cases of infectious respiratory diseases that may lead to more ER visits. Third, measuring the true exposure to air pollution is challenging. In general, air pollution is not evenly distributed within an area, and we usually do not have precise information on where the individual lives or works. Moreover, individuals may take part in some kind of avoidance behavior when pollution is high and/or the government issues a pollution alert.

To overcome the threats to identification described above, we use rich administrative data on ER visits and air pollution data covering all of Chile between 2013 and 2019. We have daily PM 2.5 measures from 75 monitors located across Chile and daily information on total ER visits by age and cause of admission for all hospitals in the country. We match the monitor information with hospitals located within a 5 km distance, so our unit of analysis is a hospital. We then estimate the effect of PM 2.5 on ER visits using OLS with hospital-month-

[1]EPA, https://www.epa.gov/pm-pollution/particulate-matter-pm-basics#PM

year fixed effects. Our key identifying assumption is that the daily variation of PM 2.5 within a particular hospital during a month in a particular year is 'as if' randomly assigned. This approach allows us to control for sorting of individuals across locations and seasonal factors that could potentially bias our results. We alleviate concerns about measurement error in exposure to air pollution by restricting our sample to hospitals within a short distance of a monitor. This allows us to have a more accurate measurement of air pollution near the hospital. If people do not travel long distances for an ER visit, then we also have a more accurate measurement of pollution exposure for the individual who visits the hospital for the emergency episode. Nonetheless, we run two additional exercises to alleviate concerns about measurement errors in air pollution. We include dummies for pollution alerts to model avoidance behavior, and we instrument air pollution using wind direction and speed.

Our results indicate that a one standard deviation increase in PM 2.5 increases respiratory visits by 1.4 percent, which is an order of magnitude larger than the same effect for the US in Deryugina et al. (2019). When we look at each age group, we find that all of them are affected by high levels of PM 2.5. We also explore the effect on ER visits by cause of admission and find that acute respiratory illnesses are the main driving force of the results for all age groups, even though chronic respiratory illnesses are also important for the 15- to 64-year-old population. We also evaluate the presence of non-linear effects of air pollution within each age group using a dummy variable for different thresholds. In general, we find that within each age group, the effect of PM 2.5 on ER visits increases monotonically when we move to higher levels of pollution.

Finally, we explore heterogeneous effects among different sources of emissions. As in many developing countries, one important source of PM 2.5 in Chile is residential wood burning for heating. We divide our sample according to the share of residential wood burning in the municipality corresponding to the monitor. We find positive effects on our outcome variable for municipalities with a share of residential wood burning emissions above 75 percent. For areas with a lower share of residential wood burning, we find positive effects smaller effects and only for some age groups. This is an important result for policy purposes, as it helps to design targeted and, thus, more effective environmental policies. Moreover, the results do not appear to be driven by higher levels of pollution in those areas. .

Our paper relates to the broad literature that studies the relation between air pollution and health outcomes (Kim (2021), Neidell (2004), Chen et al. (2013), Knittel et al. (2016), Anderson (2020), Schlenker and Walker (2015), among others). However, none of these studies focuses on PM 2.5. Some recent papers study the effects of PM 2.5 on health outcomes. Deryugina et al. (2019), using administrative Medicare data and daily pollution by US county from 1999 to 2013, study the effect of PM 2.5 exposure on elderly mortality, health care use and medical costs. They find that an increase in PM 2.5 leads to more ER visits, more hospitalizations, higher mortality, and higher inpatient spending. Ward (2015) uses daily pollution data from Ontario municipalities and studies the impact of PM 2.5 on respiratory admissions. She finds that a one standard deviation change in PM 2.5 leads to a 3.6 percent increase in respiratory admissions for children aged 0-19. She does not find any effect on the adult population. Gong et al. (2019) estimate the long-term effect of PM 2.5 on mortality in China and find that exposure to PM 2.5 causes a significant increase in all-cause and cardio-respiratory mortality, with the largest impact on individuals older than 65. .

As Deryugina et al. (2019), our paper also studies the effect of PM 2.5 on ER visits. However, unlike that study, our dataset allows us to identify the effect over a wider range of pollution levels. This is important because in many developing countries, the pollution level is much higher than in developed economies. Our data come from Chile, a middle-income country with an elevated level of air pollution. According to OECD data, the mean population exposure to PM 2.5 in Chile was 23.7 $\mu g/m^3$ in 2019; the average in the US was less than 10 $\mu g/m^3$; and the average in the OECD was 13.9 $\mu g/m^3$. Moreover, the population exposed to PM 2.5 concentrations exceeding the WHO guideline (10 $\mu g/m^3$) was 98.6 percent in Chile; the mean in the US was 5.6 percent; and the mean in the OECD was 61.7 percent. Thus, in this paper, we identify the effects of pollution at levels not considered by the related papers. This is important because, when pollution is low, it is unlikely to affect the middle-aged population. However, at higher levels, all age groups can be affected, as our results confirm.

Our study also differs in that we take the hospital as the unit of analysis and, as explained above, this allows us to reduce the measurement error in pollution exposure. In fact, in a robustness check, we run our main specification at the county level, and the results are non-significant once we include municipalities-year fixed effects. This suggests that, if we had focused our analysis at the county level, we may have underestimated the effects of pollution.

Other papers also use Chilean data to identify the effect of pollution on health outcomes. Mullins and Bharadwaj (2015) study how environmental alerts in Santiago, Chile lead to a reduction of PM 10 concentrations up to 20 percent, leading to fewer deaths among the elderly due to respiratory causes. Bharadwaj et al. (2017) examine the impact of fetal exposure to carbon monoxide (CO) on math and language skills measured in the 4th grade. They find that the 50 percent reduction in CO in Santiago between 1990 and 2005 increases lifetime earnings by approximately 100 USD per birth cohort. Rivera et al. (2021) study the effect of solar power generation in the North Region of Chile on air quality improvements and their subsequent effect on human health. They find that solar energy displaces fossil fuel generation, reducing hospital admissions due to lower respiratory diseases. Finally, Ruiz-Tagle (2019) studies the effect of PM 2.5 on ER visits in Santiago, Chile using thermal inversions and major FIFA football games to instrument for air pollution. He finds that a one standard deviation in PM 2.5 increases respiratory ER visits by 8.2 percent. Unlike the previous study, we rely on a different identification strategy and use data from all over the country.

This paper makes several contributions. First, compared to previous papers, we find a positive impact of PM 2.5 on ER visits at higher levels of air pollution. This is relevant because the marginal effect of PM 2.5 on health outcomes can be increasing in the level of air pollution or be significant for different demographic groups. Second, we use a rich administrative dataset to have a more accurate measure of pollution exposure, which helps to deal with measurement error in PM 2.5 exposure. We also show that, at least for our data, having a more accurate measurement of exposure is important. If we estimate our model using average PM 2.5 at the municipality level, our estimates become non-significant (once we control for municipality-year fixed effects). Third, we find evidence that the negative impact of PM 2.5 on health outcomes is stronger in geographic areas with a high share of emissions due to residential wood combustion. This result suggests that different emissions sources have different impacts on health outcomes, a result that can be informative for the design and implementation of environmental policies.

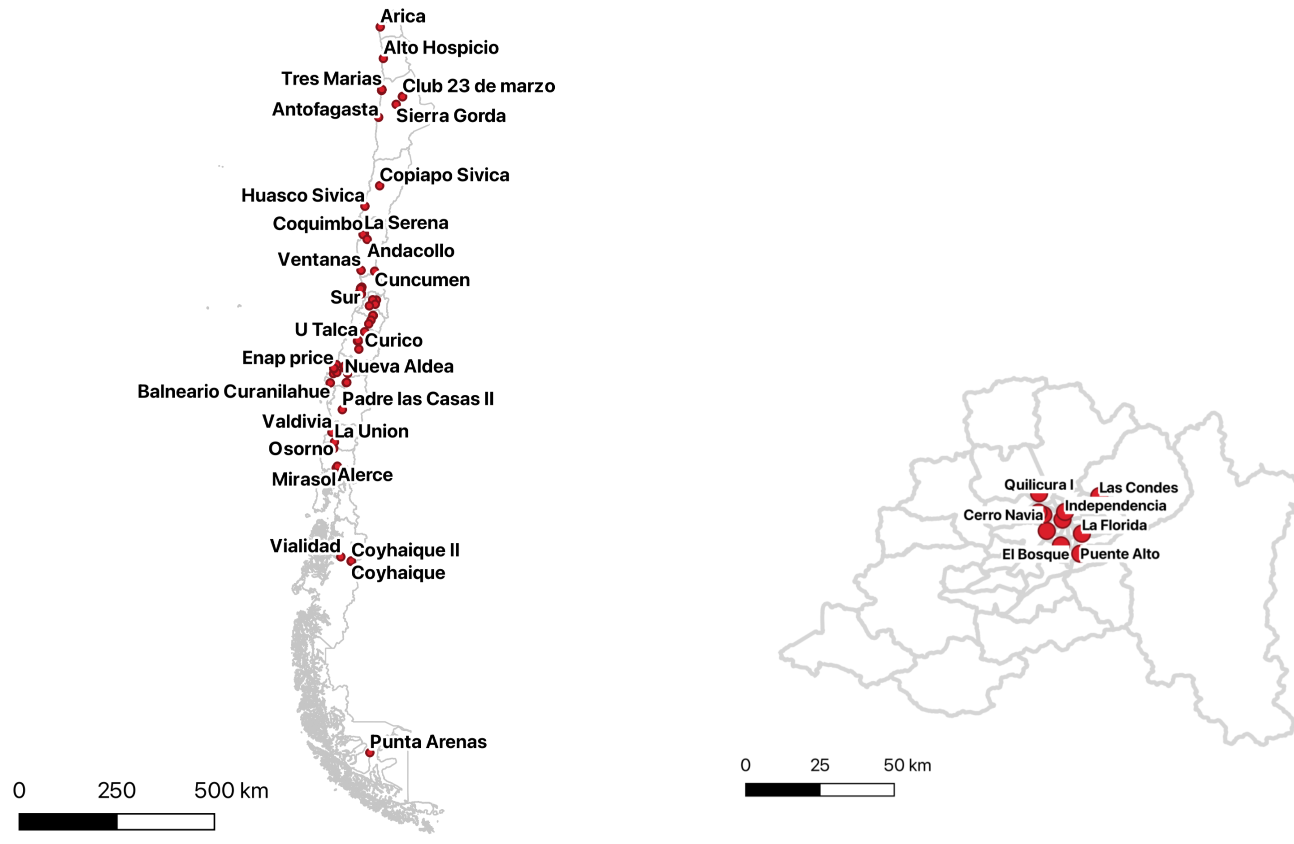
Our paper is organized as follows. Section 2 describes the data. Section 3 presents the empirical model. Section 4 discusses the results, and Section 5 studies heterogeneous effects by the share of emissions of residential wood-burning. Finally, we run a series of robustness checks in 6 and conclude in Section 7.

2 Data

2.1 Environmental Data

We use four types of data to construct our environmental variables: air pollution data, emission source data, air quality alerts and atmospheric conditions. We obtain air pollution data from the Air Quality National Information System (SINCA) of the Ministry of Environmental Affairs in Chile.[2] The SINCA collects hourly information on different pollutants, which we use to construct average daily measures of air pollution. Our main variable of interest is fine particulate matter (PM 2.5), which is measured in micrograms of particles per cubic meter ($\mu g/m^3$). We also use these data to measure other air pollutants: ozone (O_3, in parts per billion) and carbon monoxide (CO, in parts per billion). We have daily PM 2.5 information from 75 monitors during the period 2013 to 2019. The monitors are located in representative areas by population or by the level of emissions. For this reason, there are more monitors in either more-populated areas or less-populated but highly polluted areas, such as zones with high mining activity. Chile is divided into 16 regions, and there is at least one monitor in each region. Figure 1 shows the locations of monitors across Chile (part a) and in the Santiago Metropolitan Area (part b), which includes the capital city, Santiago, the country's most populated area, located in central Chile. Figure 2 shows the average PM 2.5 across Chile (part a) and in the Santiago Metropolitan Area (part b). In general, the most polluted areas are in the central part (Santiago Metropolitan Area and Valparaíso) and the south part of the country.

[2]Sistema de Informacion Nacional de Calidad del Aire.

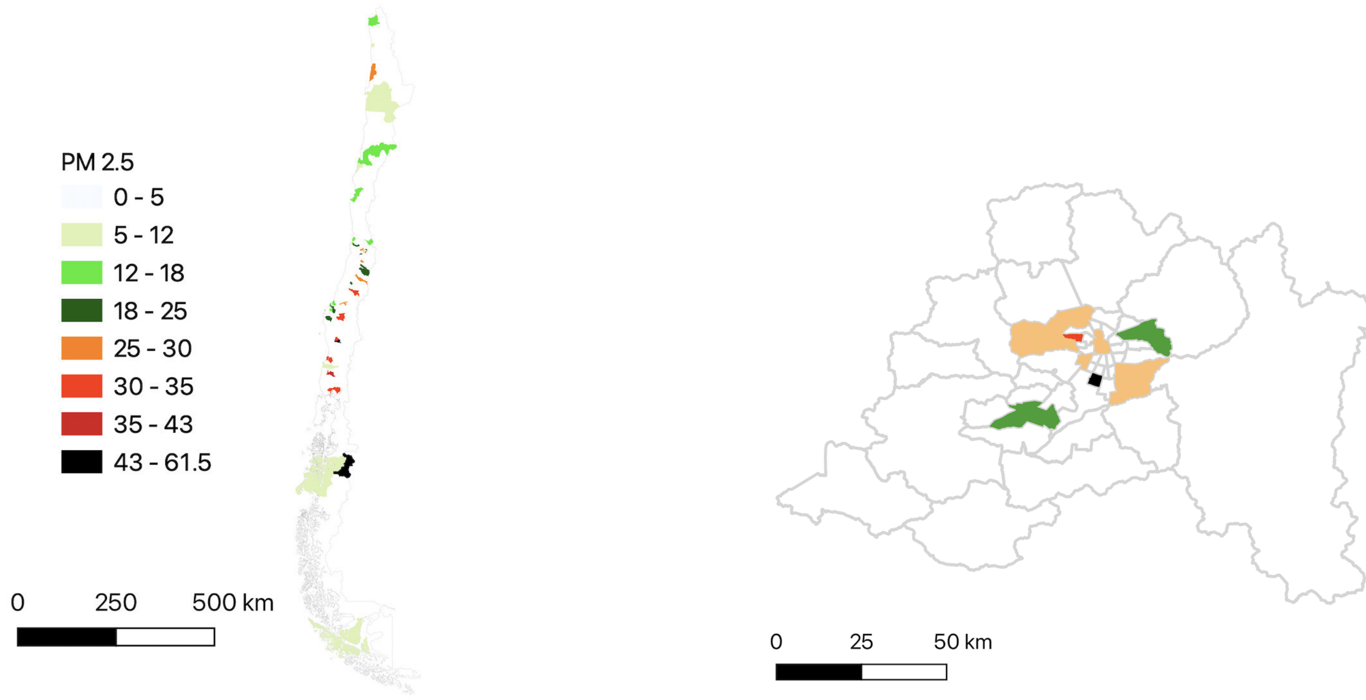


(a) All Monitors

(b) Monitors in Santiago Metropolitan Area

Figure 1: Geographic distribution of Monitors

We use the categories defined by the US Environmental Protection Agency (EPA) to classify the severity of air pollution. The EPA constructs an Air Quality Index (using 24-hour air pollution data) that can be translated into different categories of air quality: *good*, *moderate*, *unhealthy for sensitive groups*, *unhealthy*, *very unhealthy*, and *hazardous*. Table 1 shows the thresholds and the cautionary statement corresponding to PM 2.5. The categories *good* and *moderate* do not impose health risks for the general population. On the other hand, the other categories may impose health risks for some groups or the general population, and the EPA recommends some actions to reduce exposure to pollution.



(a) All municipalities (b) Municipalities in Santiago Metropolitan Area

Figure 2: Average PM 2.5 by municipality, 2013-2017

We obtain data on emission sources by municipality in 2018-2019 from the *Registro de Emisiones y Transferencias Contaminantes* (RETC). Sources are divided into stationary and non-stationary. Non-stationary sources include road transport, forest and agricultural fires, as well as residential burning of wood in rural and urban areas. Stationary sources include all non-mobile facilities or installations that emit any pollutant. Figure 3 shows PM 2.5 emission share by source and region in 2018-2019. In monitors located to the north of the Santiago Metropolitan Area and Valparaíso, the most important emission sources are road transport and stationary sources such as fossil fuel burning power plants (mainly related to mining companies).[3] In those monitors located to the south of Santiago and Valparaíso, the most important emission sources are forest and agricultural fires and residential burning of wood. Finally, in monitors located in the Santiago Metropolitan Area and Valparaíso, all emission sources are important determinants of air pollution. We exploit this heterogeneity in the sources of emissions in 5.

[3]Mining companies are located mainly in the northern region of the country.

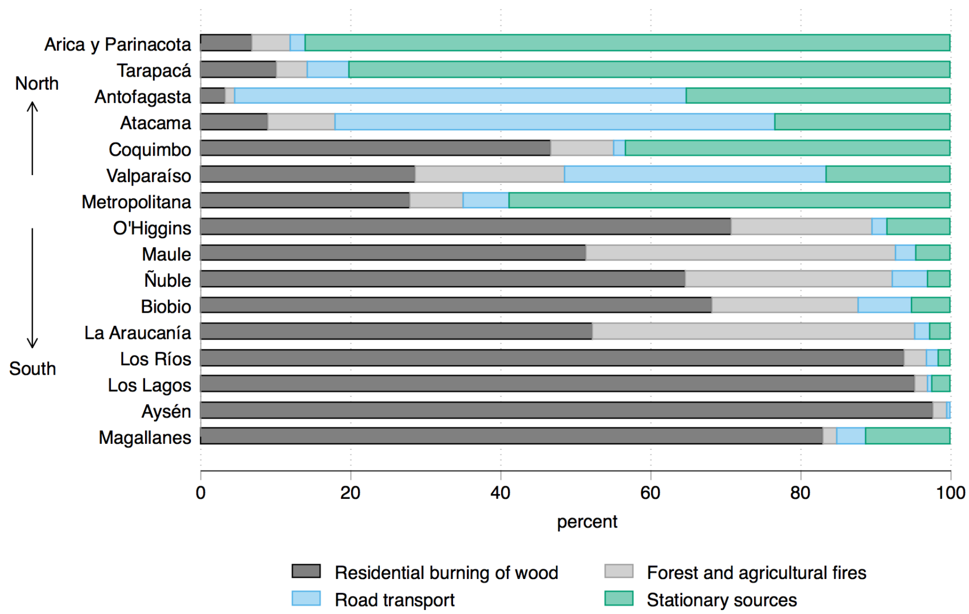


Figure 3: PM 2.5 emission share by source and region, 2018-2019

Data on air quality alerts are obtained from the *Ministry of Environmental Affairs* in Chile. The system of air pollution alerts is applied in thirteen different geographical areas located in Santiago Metropolitan Area and the south of Chile. These alerts are issued one day in advance based on a forecasting model of PM 2.5 concentrations for the following day.[4] When the forecasted PM 2.5 is equal to or higher than $80\mu g/m^3$ in any of the monitors located in a geographic area, an air quality alert is issued. Depending on the severity of the pollution episode, there are three different types of alerts. An alert episode is issued when PM 2.5 is between 80 and 109 $\mu g/m^3$; a pre-emergency episode is issued when PM 2.5 is between 110 and 169 $\mu g/m^3$; and an emergency episode is issued when PM 2.5 is higher than 170 $\mu g/m^3$. These different types of alerts trigger different protocols, including driving restrictions, prohibition of residential wood combustion and shutdown of stationary pollution emission sources, in addition to cancellation of physical exercise classes for elementary and high school students. We use these data to construct the variable *Alert*, a dummy the indicates if a PM 2.5 episode of alert, pre-emergency or emergency is issued in a given day in a monitor's location. We use these air quality alerts to control for avoidance behavior.

[4]The system of air pollution alerts is active for a fixed period during a year, but this period can vary by geographic area and over time. For example, in 2020, the system is active between May 1 and August 31 for the Santiago Metropolitan Area, and between April 1 and September 30 for Temuco and Padre de las Casas.

Finally, we obtain data on atmospheric conditions from the Center for Climate and Resilience Research. This organization collects daily minimum and maximum temperatures and precipitation for weather stations owned by the *Dirección Meteorológica de Chile* and the *Dirección General de Aguas*. We use the data from the closest weather station to compute the atmospheric conditions for each SINCA monitor.[5]

2.2 Health Data

We obtain data on ER visits from Chile's Ministry of Health.[6] The dataset includes all ER visits in Chile for the period 2008–2019 and contains daily information on the number of ER visits by cause, age group, and hospital. There are five age groups: 0-1 year, 1-4 years, 5-14 years, 15-64 years, and older than 65 years. Causes of ER visits are divided into four groups: respiratory, circulatory, external causes (traffic accidents and other external causes), and other causes. Within the respiratory group, there are several sub-groups associated with ICD-10 codes: acute upper respiratory infections (J00-J06), influenza (J09-J11), pneumonia (J12-J18), acute bronchitis or bronchiolitis (J20-J21), chronic lower respiratory diseases (J40-J46), and other respiratory causes (J22, J30-J39, J47, J60-J98).

To combine the different sources of information, we select hospitals located within a 5 km radius from a monitor as our unit of observation. We then match each hospital to the closest monitor and weather station to add air pollution and weather variables to the ER data in the hospital. By restricting our sample to hospitals within a short distance of a monitor, we have a more accurate measurement of air pollution near the hospital. If individuals do not travel long distances for ER visits, then we also have a more accurate measurement of pollution exposure for the individuals who visit the ER. We select the period 2013–2019 because few monitors measure PM 2.5 before 2013.

Table 2 shows the number of monitors and hospitals in our sample by year. The number of monitors has increased over time. As a consequence, the number of hospitals we can match to a monitor has increased, as well.[7] In terms of the number of hospitals per

[5] The data on atmospheric conditions are publicly available from http://www.cr2.cl/recursos-y-publicaciones/bases-de-datos/. There are 295 stations that report hourly temperature and 816 stations that report hourly precipitation.

[6] Data are available from the *Departamento de Estadísticas e Información de la Salud* (DEIS) at https://deis.minsal.cl.

[7] In Section 6, we confirm that our results are not driven by entry/exit of monitors. We drop from our sample those hospitals linked to monitors that enter/exit during the period and estimate our main model in this balanced sample, finding similar results.

monitor, two thirds of the monitors are matched with three or fewer hospitals, but a few monitors located in more-populated areas are matched to ten or more hospitals.

Table 3 shows summary statistics of our sample. There are 2,396,905 observations. The average concentration of PM 2.5 is 25.66. In terms of the Air Quality Index, this means that almost 30 percent of the observations correspond to good air quality, 50 percent of the observations to moderate air quality, and 20 percent to worse-than-moderate air quality. There is an air pollution alert (alert, pre-emergency or emergency) in 9.4 percent of the observations. The average number of daily ER visits per hospital is 26, and around 30 percent of these ER visits are for respiratory conditions. Finally, the average maximum temperature is 21 degrees Celsius; the average minimum temperature is 9 degrees Celsius; the average precipitation is .80 mm; and the average wind speed is 1.52 km per hour.

Figure 4 shows the average daily respiratory ER visits (above) and the average daily PM 2.5 (below). Note that both variables are highly seasonal. In the case of PM 2.5 during the winter months, the average daily pollution is above 50. Also, from the figure, we can note a strong correlation between both variables.

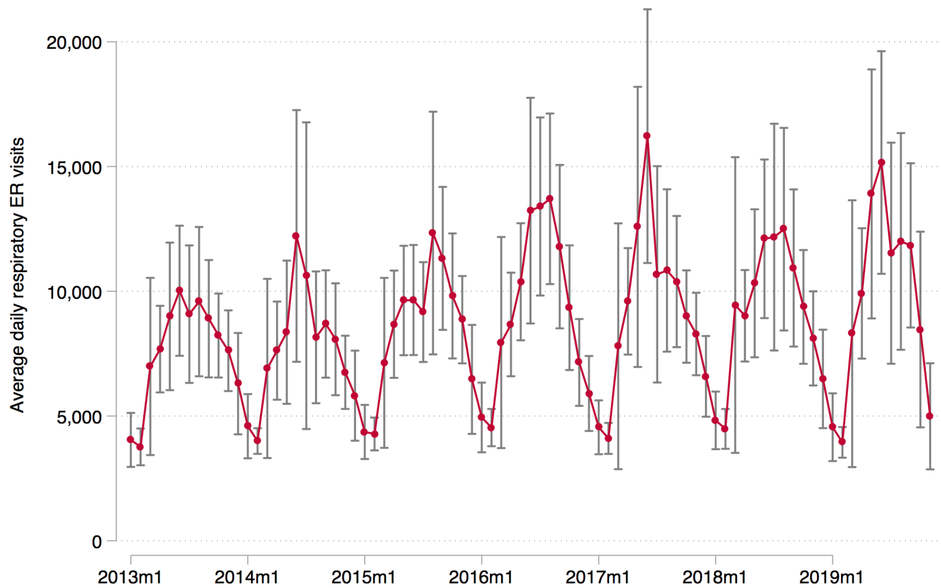
Finally, Table 4 shows the decomposition of the between-variation and within-variation of two variables: PM 2.5 and the deviation of the PM 2.5 with respect to the mean. The between-variation is the variation experienced by the variables across hospitals, while the within-variation represents the variation within a hospital across time. As we can observe from the table, the within-variation is higher than the between-variation. Having enough within-variation is important for our estimation strategy since we exploit the daily PM 2.5 variation within each hospital, as we explain in detail in the next section.

3 Empirical Strategy

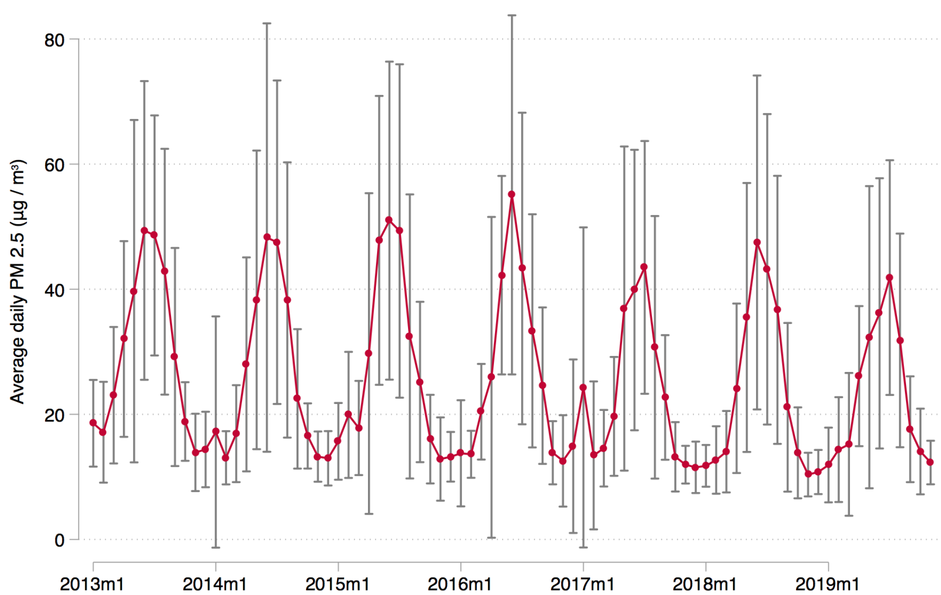
We estimate the effect of short-term exposure to fine particulate matter on ER visits using the following model:

$$Y_{hadmy} = \beta_0 + \beta_1 PM2.5_{hdmy} + X'_{hdmy}\gamma + \alpha_a + \alpha_{hmy} + \alpha_{dmy} + \epsilon_{hadmy}, \qquad (1)$$

where Y_{hadmy} is the logarithm of ER visits for age group a in hospital h on day d in month m and year y; $PM2.5_{hdmy}$ is the fine particulate level in hospital h on dmy; X_{hdmy}



(a) Respiratory ER visits



(b) Average daily PM 2.5 concentration

Figure 4: Air pollution and respiratory ER visits, 2013-2018

are weather variables (daily max and min temperature and precipitation) in hospital h on dmy; α_a is an age group fixed effect; α_{hmy} is an hospital-month-year fixed effect; α_{dmy} is an day-month-year fixed effect; and ϵ_{hadmy} captures unobservables that affect the outcome variable. Our parameter of interest is β_1, the coefficient on PM 2.5. In one of our baseline specifications, we also include a dummy variable for air quality alerts and its interaction with the deviation of PM 2.5 with respect to 80 $\mu g/m^3$ (the PM 2.5 level that activates the alert).[8] This allows us to control for avoidance behavior.

We estimate equation (1) by OLS with standard errors clustered at the monitor level.

The variation in our data allows us to include a full set of hospital-month-year fixed effects. Thus, identification comes from daily variations in pollution in a particular hospital within a month in a particular year. This approach allows us to control for two important factors that could potentially bias our estimates. First, there are seasonal factors that can be correlated with both pollution and respiratory conditions. In most regions in Chile, the level of pollution increases in winter because of the use of contaminating heating fuels such as wood. However, the incidence of respiratory conditions also increases in winter, and we need to control for this confounding factor. Moreover, this source of endogeneity could be more important for regions that rely more on wood as heating fuel. The interaction between month-year and hospital control for this confounding factor. It also allows us to control for the potential differences between areas in a particular season. Second, the residential choice could create a sorting equilibrium such that wealthier individuals choose to live in less-polluted areas and have better health. The hospital-month-year fixed effects could control for this sorting, even if it changes over time because some areas become less polluted and change the residential choice for some families.[9]

OLS estimates of equation (1) could be biased if there is measurement error in exposure to PM 2.5, or if the daily allocation of PM 2.5 within a hospital-month-year cell is not as good as randomly assigned.

There could be measurement error in exposure to PM 2.5 for two reasons. First, the daily measures of PM 2.5 levels at the monitor location could differ from the real exposure for individuals who visit the ER. To minimize this source of measurement error, we choose hospitals located within a 5 km radius from a monitor. Because we focus on emergency

[8]Using the deviation of PM 2.5 with respect to 80 $\mu g/m^3$ only facilitates the interpretation for the *Alert* dummy but does not affect the other estimated coefficients in the regression.

[9]We also include day-month-year fixed effects that control for any common temporal factor (such as weekends or holidays) that can potentially affect both pollution and ER visits for all hospitals.

episodes, we expect that the place of residence or work should be a short distance from the hospital. Second, on days with a high level of air pollution, individuals can engage in some kind of avoidance behavior to mitigate exposure to pollution. In Chile, the government issues air pollution alerts when air quality is above some threshold. These alerts activate a series of traffic bans and recommendations for avoiding exposure to air pollution. In our preferred specification, we interact dummies for a pollution alert with PM 2.5 to capture this avoidance behavior.

Regarding the possible endogeneity of the allocation of PM 2.5 within a hospital-month-year cell, we follow recent papers (Ward (2015) and Deryugina et al. (2019)) and use wind direction and velocity to instrument the level of PM 2.5. This instrument satisfies the exclusion restriction because it is unlikely to have a direct effect on ER visits. Moreover, because the level of fine particulates depends on weather conditions such as wind, our instrument is correlated with air pollution. The specification for the first stage of the IV is

$$\begin{aligned} PM2.5_{hdmy} = & \sum_{b=0}^{2} \pi_{1,b} wind\, direction^{b}_{hdmy} + \pi_2 wind\, speed_{hdmy} \\ & \sum_{b=0}^{2} \pi_{3,b} wind\, direction^{b}_{hdmy} \times wind\, speed_{hdmy} \\ & + X'_{hdmy}\theta + \alpha_a + \alpha_{hmy} + \alpha_{dmy} + \epsilon_{hadmy}, \end{aligned} \tag{2}$$

where $wind\, speed_{hdmy}$ is the average daily wind speed in hospital h on date dmy and $wind\, direction^{b}_{hdmy}$ is equal to 1 if the average daily wind direction in hospital h on date dmy falls in the interval [90b,90b+90] and 0 otherwise. To simplify the construction of our instrument, we partition wind direction in 90-degree intervals and use the interval [270, 360] as the reference point. Our instrument exploits the effect of wind direction and wind speed, allowing for wind speed to have a different effect depending on its direction.

In the robustness section, we also allow for a non-linear effect of PM 2.5 on ER visits. In particular, we use dummy variables defined over the thresholds of PM 2.5 presented in the previous section (Table 1).

4 Results

Table 5 shows the OLS estimates of equation (1). The two first columns in the table show a basic specification without hospital-month-year interaction and the two last columns our preferred specification with these interactions, with similar results. Moreover, columns (2) and (4) of Table 5 include the dummy variable for air quality alerts to control for avoidance behavior. We estimate that an increase in 1 $\mu g/m^3$ in PM 2.5 increases respiratory ER visits from 0.03 to 0.06 percentage points. Notice, also, that our coefficients double when we control by the alerts, which may suggest that avoidance behavior downward biases our estimates for the basic specification. This result is consistent with Kim (2021), who finds that the estimate on respiratory hospital admission is three times larger when controlling for avoidance behavior. The estimated effect is not negligible: a one standard deviation increase in PM 2.5 increases respiratory ER visits by 1.44 percentage points. Our results are an order of magnitude larger than Deryugina et al. (2019), who find that an increase of one standard deviation in PM 2.5 increases ER visits by 0.05 percent in the US.[10] This difference might be due to the higher level of overall pollution in our data, which leads to bigger effects.

Using our preferred specification, which includes alerts and hospital-month-year interactions, we explore heterogeneous effects by age group in Table 6. As we observe from the table, an increase in PM 2.5 causes a similar increase in respiratory ER visits for each age group. In particular, we find that a 1 $\mu g/m^3$ increase in PM 2.5 leads to a 0.04 percent increase in ER visits for the aged 15-64 population. The last result is important. The middle-aged population constitutes the biggest group, so any positive effect on ER visits also has a greater impact on the health system. This result differs from Ward (2015), who does not find any effect on hospital admissions for the population over age 20. A plausible explanation is that, at higher levels of pollution, every age group can be affected by more PM 2.5.

We evaluate the presence of non-linear effects of air pollution using a specification with dummy variables for the different thresholds defined in Table 1.[11] Figure 5 shows the estimated effects by age group. We find that, within an age group, ER visits increase monotonically when we move to higher levels of pollution. An exception to this rule are

[10] This comparison uses the OLS estimates in Deryugina et al. (2019), but there are similar differences if we compare the IV estimates in Deryugina et al. (2019) with ours.

[11] Our sample has few observations in which air quality is considered 'hazardous,' so we combine 'hazardous' and 'very unhealthy' in the same dummy variable.

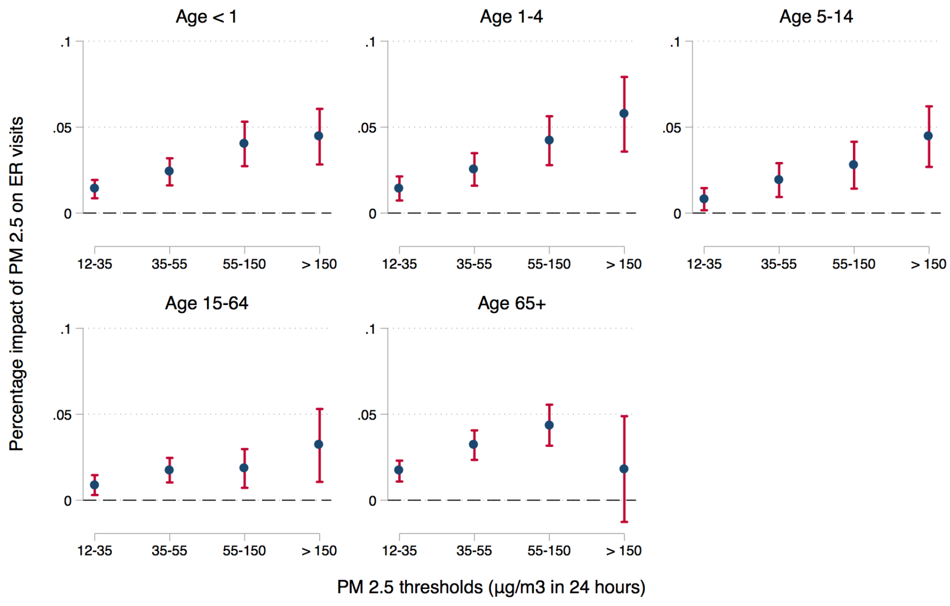


Figure 5: Effect of PM 2.5 thresholds on (log) respiratory ER visits, by age group

adults older than 65 who experience a decrease in ER visits when PM 2.5 is above 150 $\mu g/m^3$. This may be due to more precautionary behavior for this group, as they are usually more prone to respiratory problems.

Table 7 reports OLS and IV estimates using wind direction and speed to instrument for PM 2.5 and its interactions with *Alert* to instrument for $PM\,2.5 \times Alert$ (see equation (2) for more details).

Note that, because not all monitors report wind direction and speed, this sample is smaller, consisting of 50 monitors and 1,756,720 observations. Columns 1 and 3 show the results for the basic model, and columns 2 and 4 show the results for the model with alerts. Because the results are similar across the different specifications, we focus on our preferred specification with alerts. The test of weak instruments in the first stage has an F-stat of 23.1 for $PM\,2.5$ and 26.6 for $PM\,2.5 \times Alert$, showing that the instruments satisfy the relevant condition necessary for identification in the IV estimation. IV estimates imply that a 1 $\mu g/m^3$ increase in PM 2.5 causes a 0.19 percent increase in respiratory ER visits. These results are three times larger than the OLS estimates[12] Using our preferred specification, Table 8 reports the IV estimates by age group. IV estimates also suggest that all age groups

[12] Deryugina et al. (2019) and Ward (2015) obtain a similar upward correction in the IV estimates.

are negatively affected by air pollution, but these effects are magnified compared with OLS.

Table 9 explores the effect of PM 2.5 on different causes for respiratory ER visits. We split total respiratory ER visits into acute (J00-J21), chronic (J40-J46), and other respiratory conditions. The effects of PM 2.5 on acute respiratory ER visits are positive and significant for all age groups (Panel B). However, chronic respiratory ER visits seem to be an important cause only for the aged 15-64 population and not for the other age groups (Panel C). Finally, other respiratory causes are significant only for the population older than 65.

5 Heterogeneous Effects by Different Sources of Emissions

In this section, we explore heterogeneous effects among different sources of emissions on our outcome variable. Different emission sources can emit particulate matter that can differ in size and composition, with potentially different effects on health outcomes. We focus on emissions due to residential burning of wood. This is important for several reasons.

First, as in many developing countries, residential use of wood for heating is an important source of PM 2.5 in Chile. Moreover, there is regional variation that we can exploit in our estimation. In particular, the south-central region of the country uses more wood for heating because of its lower winter temperatures. In fact, around 90 percent of total emissions in the south-central region of the country are generated by wood combustion (Chávez et al. (2011)).

Second, residential wood combustion produces a large portion of ultrafine particles—i.e., particles with a diameter smaller than one micrometer—which are considered the most harmful to human health (Díaz-Robles et al. (2014)). These ultrafine particles have a higher surface-to-volume ratio than larger particles, allowing them to transport large quantities of toxic pollutants (Díaz-Robles et al. (2014) and Trojanowski and Fthenakis (2019)).

Third, previous literature documenting the negative effect of residential wood combustion on health outcomes in developing countries (Chakraborty et al. (2020); Hanna et al. (2016); Fullerton et al. (2008)) focus on its effects through an increase in indoor pollution. This is not the main channel for Chile though. Since 2007, Chile's Government has implemented different policies to replace old stoves with less-polluting ones. These new models are highly efficient in reducing indoor pollution, but they still have a highly polluting combustion process that generates outdoor pollution (Ruiz-Tagle and Schueftan (2019); Schueftan and González (2015)). After the replacement program, implementation emissions continued to increase in the areas where wood combustion is the main source of emissions (Schueftan and González (2015)). Whether there are negative effects of residential wood burning on health outcomes without increasing indoor pollution is an open question.

To estimate the effect of PM 2.5 by sources of emissions, we use data on total PM 2.5 emissions by source for each municipality in the country for the period 2018-2019. Using these data, we construct the share of *residential emissions* (i.e., residential burning of wood in rural and urban areas) at the municipality level. This variable is time-invariant (average share in the municipality over the period 2018-2019) and aims at capturing municipalities that rely on wood-burning for heating.

Using the share of *residential emissions*, we divide our sample into three different groups: (i) hospitals located in municipalities with a share of residential emissions less than 50 percent of the total; (ii) hospitals in municipalities with a share of residential emissions between 50 and 75 percent; and (iii) hospitals in municipalities with a share of residential emissions greater than 75 percent. We run our basic specification by age group for each of these groups.

Table 10 shows the results. For municipalities with a share of *residential emissions* below 50 percent (Panel A) we find a positive and significant effect for the the adult and the elderly population (15-64 and 65 or more years old). For municipalities between 50 percent and 75 percent (Panel B), we find no significant effect of PM 2.5 on ER visits, except for the elderly. For municipalities with a share of *residential emissions* above 75 percent, however, we find a positive effect of air pollution on ER visits for all age groups. An increase of 1 $\mu g/m^3$ in PM 2.5 leads to between a 0.03- and a 0.07-percent increase in ER visits, depending on the age group. To summarize, we find that effect of PM 2.5 on ER visits is higher and affects more age groups in municipalities with a high share of residential emissions. The results show that residential emissions play an important role in this type of health impact.

A possible concern about the share of *residential emissions* is that it also captures differences in levels of air pollution because municipalities that rely more on wood burning for heating also have higher levels of air pollution. To alleviate this concern, we explicitly estimate heterogeneous effects by the level of pollution. We compute the average PM 2.5 between 2013 and 2019 at the hospital level and divide hospitals into three terciles. Table 11 shows these results: when the average pollution is low (less than 23 $\mu g/m^3$), the impact on ER visits is positive and significant for the adult and the elderly populations (15-64 and 65 or more years old). When we consider intermediate average levels of pollution (between 23 $\mu g/m^3$ and 30 $\mu g/m^3$), all age groups are affected. When we move to a higher average pollution level (more than 30 $\mu g/m^3$), either young children (four years old or younger) or senior citizens are affected. Moreover, we observe that the average impact on ER visits decreases when the average level of pollution increases. Thus, since there is a different pattern in the effects of PM 2.5 on ER visits by share of residential emissions or by the level of pollution, we do not find that our results on *residential emissions* in Table 10 are driven by higher pollution levels.

6 Robustness Checks

In this section, we run several robustness exercises to evaluate the sensitivity of our results.

First, we explore the dynamic effects of PM 2.5 in Figure 6. This figure shows that, for each age group, there is an immediate effect (same day) of PM 2.5 on respiratory ER visits, but there are no effects on respiratory ER visits during the subsequent days. The fact that the coefficients on the lags of PM 2.5 are not significant also suggests that fine particulates do not merely anticipates ER visits that would have taken place regardless of the pollution level. In addition, the coefficients on the leads PM 2.5 are not significant, giving some credibility to our identification strategy because we should not expect an effect of future pollution on ER visits today.

Second, one of the contributions of our work is that we have a more accurate measure of pollution exposure because we link hospitals to monitors within a 5 km distance. To show that measurement error can be an issue when working at the municipality level, we estimate our preferred specification at this level. Tables 12 and 13 in the online appendix show the results of this exercise. In Table 12, we find positive and significant effects in the specification with municipality fixed effects (columns 1 and 2). However, the effects become non-significant once we control for municipality-year fixed effects (columns 3 and 4) municipality-month-year fixed effects. Table 13 shows the specification with municipality-month-year fixed effects by age group. We find do not find any effect for each of the age groups.

Third, a concern about our estimates is that PM 2.5 can be correlated with other pollutants and that the negative effects attributed to PM 2.5 are partially due to these other

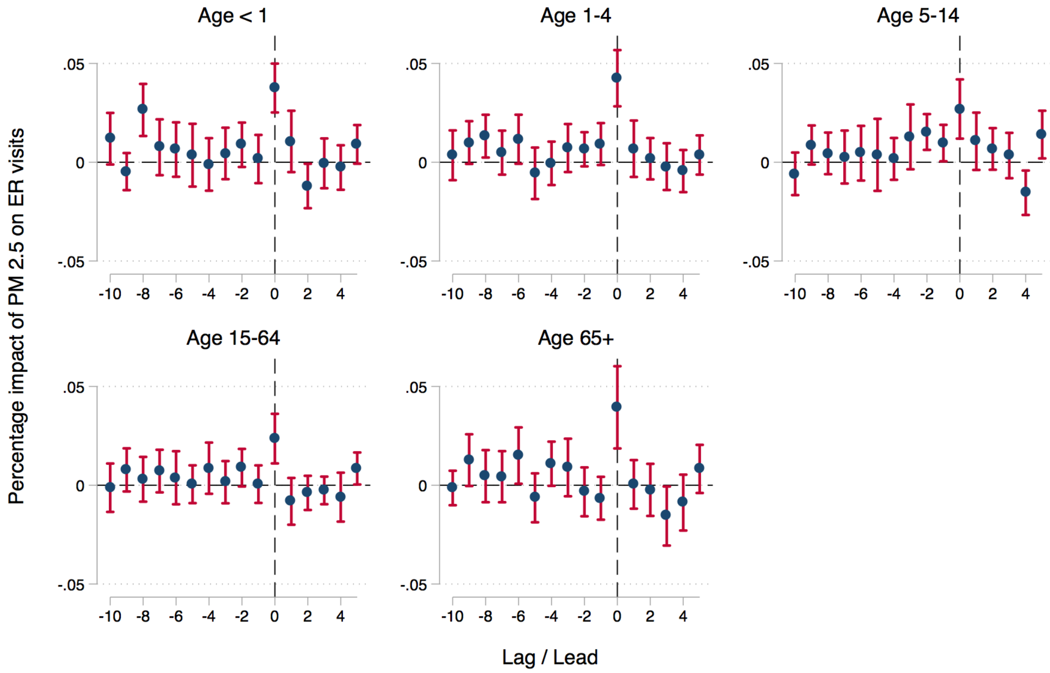


Figure 6: Dynamic effect of PM 2.5 on (log) respiratory ER visits, by age group

pollutants. We estimate a specification that includes CO and Ozone with two lags for every pollutant considered. We restrict our sample to monitors that have readings for all the pollutants. Table 14 shows the results for this specification. Notice that coefficients for both CO and Ozone are not significant, and the effect of PM 2.5 on respiratory ER visits barely changes once we control for these pollutants. We conclude that our results are not driven by other pollutants.

Fourth, we run some falsification tests using non-respiratory ER visits that are less likely to be affected by air pollution. Table 15 reports the results for ER visits due to respiratory illnesses (Panel A), circulatory illnesses (Panel B), and traffic accidents (Panel C). We do not find any significant effect on ER visits due to circulatory illnesses or traffic accidents.

Fifth, in our main sample, the number of monitors increases from 58 in 2013 to 75 in 2019. To alleviate any concern that our results are driven by the entry of new monitors, we construct a new sample keeping the number of monitors and hospitals constant over time. The results reported in Tables A.1 and A.2 in the online appendix show that the effects are similar for this sample.

Finally, the effect of weather variables on ER visits can be nonlinear. We estimate a new specification controlling for a more flexible form in the weather variables. We divide daily maximum temperatures into 16 bins, daily minimum temperatures into 16 bins, and daily precipitation into 5 bins. We then create a set of dummy variables for all possible interactions of these bins. The results reported in Tables A.3 and A.4 in the online appendix show that we find similar results to our main specification.

7 Conclusion

Pollution has become a hazard worldwide, affecting the health of the population. Studying the causal relationship between pollution and different health outcomes is important, as it makes it possible to address the true costs of contamination and, therefore, to design optimal environmental policies. One important source of pollution is particulate matter. PM 2.5 are tiny particulates that, when inhaled, can cause a variety of health problems. In this paper, we study the impact of PM 2.5 on respiratory ER visits. We use data from Chile, which is a middle-income, highly polluted country. Unlike the approach in some previous papers in the literature, this allows us to study the impact of PM 2.5 over a wide range of pollution levels. This is important because when pollution is low, it may not affect the whole population but only the more sensitive groups, such as the elderly. However, when we move to higher levels of contamination, all age groups are affected.

Our detailed dataset allows us to control for some well-documented problems in this literature: sorting of individuals; seasonal factors; and measurement error due to the unknown true exposure level and avoidance behavior. To reduce the measurement error, we match each pollution monitor with hospitals within a 5 km distance. If people do not travel long distances for an ER visit, then we also have a more accurate measurement of individuals' exposure to pollution. We also include dummies for pollution alerts to model avoidance behavior, and we instrument air pollution using wind direction and speed. Our identification strategy relies on the daily variation of PM 2.5 in a hospital in a given month-year, which allows us to control for seasonal factors and the sorting of individuals.

We find that an increase of one standard deviation in PM 2.5 increases respiratory visits by 1.4 percent. According to the findings of Deryugina et al. (2019), this is an order of magnitude larger than evidence from the US. This difference might be due to the higher level of overall pollution in our data leading to bigger effects. We also explore heterogeneous effects by age groups and find that an increase in PM 2.5 causes a similar increase in respiratory ER visits. We also explore heterogeneous effects among different sources of emissions. We find positive effects on our outcome variable for municipalities with residential wood-burning emissions above 75 percent. Our results are robust to controlling for other pollutants; to falsification tests using non-respiratory ER visits that are not likely to be related to air pollution; to fixing the number of monitors; and to different specifications for the weather variable.

References

Anderson, M. L. (2020). As the wind blows: The effects of long-term exposure to air pollution on mortality. *Journal of the European Economic Association 18*(4), 1886–1927.

Anenberg, S. C., D. K. Henze, V. Tinney, P. L. Kinney, W. Raich, N. Fann, C. S. Malley, H. Roman, L. Lamsal, B. Duncan, R. V. Martin, A. van Donkelaar, M. Brauer, R. Doherty, J. E. Jonson, Y. Davila, K. Sudo, and J. C. Kuylenstierna (2018). Estimates of the global burden of ambient PM2.5, Ozone, and NO2 on asthma incidence and emergency room visits. *Environmental Health Perspectives 126*(10), 107004.

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

Chakraborty, R., J. Heydon, M. Mayfield, and L. Mihaylova (2020). Indoor air pollution from residential stoves: Examining the flooding of particulate matter into homes during real-world use. *Atmosphere 11*(12).

Chávez, C., J. Stranlund, and W. Gomez (2011). Controlling urban air pollution caused by households: uncertainty, prices, and income. *Journal of Environmental Management 92*(10), 2746–53.

Chen, Y., A. Ebenstein, M. Greenstone, and H. Li (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River policy. *Proceedings of the National Academy of Sciences 110*(32), 12936–12941.

Clay, K., N. Z. Muller, and X. Wang (2021). Recent increases in air pollution: Evidence and implications for mortality. *Review of Environmental Economics and Policy 15*(1), 154–162.

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

Díaz-Robles, L. A., J. S. Fu, A. Vergara-Fernández, P. Etcharren, L. Schiappacasse, G. Reed, and M. Silva (2014). Health risks caused by short term exposure to ultrafine particles generated by residential wood combustion: a case study of temuco, chile. *Environment international 66*, 174–81.

Fullerton, D. G., N. Bruce, and S. B. Gordon (2008). Indoor air pollution from biomass fuel smoke is a major health concern in the developing world. *Transactions of the Royal Society of Tropical Medicine and Hygiene 102*(9), 843–851.

Gong, Y., S. Li, N. Sanders, and G. Shi (2019, May). The mortality impact of fine particulate matter in China.

Hanna, R., E. Duflo, and M. Greenstone (2016, February). Up in smoke: The influence of household behavior on the long-run impact of improved cooking stoves. *American Economic Journal: Economic Policy 8*(1), 80–114.

Kim, M. J. (2021). Air pollution, health, and avoidance behavior: Evidence from South Korea. *Environmental and Resource Economics 79*(1), 63–91.

Kloog, I., B. Ridgway, P. Koutrakis, and B. A. Coull (2013). Long- and short-term exposure to PM2.5 and mortality: using novel exposure models. *Epidemiology 24*(4), 555–61.

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

Mullins, J. and P. Bharadwaj (2015). Effects of short-term measures to curb air pollution: Evidence from Santiago, Chile. *American Journal of Agricultural Economics 97*(4), 1107–1134.

Neidell, M. J. (2004, November). Air pollution, health, and socio-economic status: the effect of outdoor air quality on childhood asthma. *Journal of Health Economics 23*(6), 1209–1236.

Peel, J. L., P. E. Tolbert, M. Klein, K. B. Metzger, W. D. Flanders, M. Todd, K., P. B. J. A., Ryan, and H. Frumkin (2005). Ambient air pollution and respiratory emergency department visits. *Epidemiology 16*(2), 164–174.

Rivera, N. M., C. Ruiz-Tagle, and E. Spiller (2021, February). The health benefits of solar power generation: Evidence from Chile. Working Paper EDF EDP 21-02, Environmental Defense Fund.

Ruiz-Tagle, J. C. (2019, January). Causal effects of ambient air pollution on health: Evidence from Santiago, Chile. Working paper.

Ruiz-Tagle, J. C. and A. Schueftan (2019). Reducing air pollution through behavioral change of wood-stove users: Evidence from an rct in valdivia, chile. Inter-american development bank working paper series nÂº idb-wp-959.

Sanderson, E. and F. Windmeijer (2016). A weak instrument f-test in linear iv models with multiple endogenous variables. *Journal of Econometrics 190*(2), 212 – 221. Endogeneity Problems in Econometrics.

Schlenker, W. and W. R. Walker (2015, 10). Airports, air pollution, and contemporaneous health. *The Review of Economic Studies 83*(2), 768–809.

Schueftan, A. and A. D. González (2015). Proposals to enhance thermal efficiency programs and air pollution control in south-central chile. *Energy Policy 79*, 48–57.

Szyszkowicz, M., T. Kousha, J. Castner, and R. Dales (2018). Air pollution and emergency department visits for respiratory diseases: A multi-city case crossover study. *Environmental Research 163*, 263–269.

Trojanowski, R. and V. Fthenakis (2019). Nanoparticle emissions from residential wood combustion: A critical literature review, characterization, and recommendations. *Renewable and Sustainable Energy Reviews 103*, 515–528.

Ward, C. J. (2015). It's an ill wind: The effect of fine particulate air pollution on respiratory hospitalizations. *The Canadian Journal of Economics / Revue canadienne d'Economique 48*(5), 1694–1732.

Zanobetti, A. and J. Schwartz (2006). Air pollution and emergency admissions in Boston, MA. *Journal of epidemiology and community health 60*(10), 890–5.

Appendix: Tables

Table 1: Air Quality Index Thresholds for PM 2.5 (in average $\mu g/m^3$ in 24 hours) and Cautionary Statement

Air Quality Category	PM 2.5	Cautionary Statement
Good	0-12	
Moderate	12.1-35.4	Unusually sensitive people should consider reducing prolonged or heavy exertion.
Unhealthy for Sensitive Groups	35.5-55.4	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should reduce prolonged or heavy exertion.
Unhealthy	55.5-150.4	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should avoid prolonged or heavy exertion; everyone else should reduce prolonged or heavy exertion.
Very Unhealthy	150.5-250-4	People with heart or lung disease, older adults, children, and people of lower socioeconomic status should avoid all physical activity outdoors. Everyone else should avoid prolonged or heavy exertion.
Hazardous	250.5-500.4	Everyone should avoid all physical activity outdoors; people with heart or lung disease, older adults, children, and people of lower socioeconomic status should remain indoors and keep activity levels low.

Note: Source: US EPA.

Table 2: Number of monitors and hospitals by year

Year	Number of Monitors	Number of Hospitals
2013	58	196
2014	59	201
2015	66	221
2016	69	249
2017	74	259
2018	73	265
2019	75	267

Table 3: Summary statistics, 2013–2019

Variables	Mean	s.d.
Pollution		
PM 2.5 (μg / m^3)	25.66	24.12
Good (0-12)	0.289	0.453
Moderate (12.1-35.4)	0.496	0.500
Unhealthy sensit. (35.5-55.4)	0.123	0.329
Unhealthy (55.5-150.4)	0.087	0.282
Very unhealthy (150.5-250.4)	0.004	0.063
Hazardous (250.5+)	0.001	0.023
CO (parts per billion)	0.72	0.62
Ozone (parts per billion)	13.05	7.47
Alert	0.094	0.292
ER visits		
Total	26.38	35.52
Respiratory	7.89	9.51
Acute respiratory (J00-J21)	6.70	8.42
Chronic respiratory (J40-J46)	0.44	1.23
Circulatory	0.55	1.71
External causes	3.13	9.04
Weather		
Max. Daily Temp. (Celsius)	20.67	6.64
Min. Daily Temp. (Celsius)	8.91	4.79
Daily precipitation (mm)	0.80	45.28
Wind Speed (km/hour)	1.52	0.83
Observations	2,396,905	

Table 4: Overall, between and within variation in PM 2.5, 2013–2019

		Mean	Std Dev	Min	Max	N/n/T-bar
PM 2.5 (μg / m^3)	overall	25.66	24.12	0.00	770.75	479,381
	between	.	17.56	0.00	380.00	16,661
	within	.	16.67	-152.91	722.96	29

Table 5: Effect of PM 2.5 on (log) respiratory ER visits

	(1)	(2)	(3)	(4)
PM 2.5, same day (μg / m^3)	0.0003***	0.0006***	0.0003***	0.0006***
	[0.0001]	[0.0002]	[0.0001]	[0.0001]
Alert		-0.0057		-0.0081*
		[0.0095]		[0.0048]
PM 2.5 × Alert		-0.0006***		-0.0005***
		[0.0002]		[0.0001]
Hospital-Month-Year FE	No	No	Yes	Yes
Mean DV	7.715	7.715	7.715	7.715
R-squared	0.551	0.551	0.574	0.574
Observations	2,308,060	2,308,060	2,308,060	2,308,060

Note: This table reports OLS estimates of equation (1). The dependent variable is the logarithm of respiratory ER visits. All specifications include age group, hospital and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Columns (2) and (4) include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table 6: Effect of PM 2.5 on (log) respiratory ER visits, by age group

	(1)	(2)	(3)	(4)	(5)
	<1	1-4	5-14	15-64	65 +
PM 2.5, same day (μg / m^3)	0.0005***	0.0007***	0.0005***	0.0004***	0.0008***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Alert	0.0003	-0.0125*	-0.0056	-0.0077	-0.0153**
	[0.0068]	[0.0072]	[0.0073]	[0.0051]	[0.0065]
PM 2.5 $\times$ Alert	-0.0003**	-0.0005***	-0.0002**	-0.0004***	-0.0008***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0002]
Mean DV	3.176	8.824	7.914	15.835	2.827
R-squared	0.659	0.753	0.718	0.787	0.523
Observations	461,581	461,581	461,581	461,581	461,581

Note: This table reports OLS estimates of equation (1) by age group. The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 7: OLS and IV estimates of the effect of PM 2.5 on (log) respiratory ER visits

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5, same day (μg / m^3)	0.0003***	0.0006***	0.0013***	0.0019***
	[0.0000]	[0.0001]	[0.0002]	[0.0004]
Alert		-0.0100*		-0.0562***
		[0.0052]		[0.0149]
PM 2.5 × Alert		-0.0005***		-0.0014***
		[0.0001]		[0.0005]
F stat PM 2.5 (weak inst.)			24.5	23.1
p-value PM 2.5 (weak inst.)			0.000	0.000
F stat PM 2.5 × Alert (weak inst.)				26.6
p-value PM 2.5 × Alert (weak inst.)				0.000
Mean DV	8.038	8.038	8.038	8.038
Observations	1,756,720	1,756,720	1,756,720	1,756,720

Note: This table reports OLS and IV estimates of equation (1). The dependent variable is the logarithm of respiratory ER visits. The instruments for $PM2.5$ are wind direction and speed and its interactions (see equation(2) for more details), and the instruments for $PM2.5 \times Alert$ are the same instruments interacted with *Alert*. All specifications include hospital-month-year and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Columns (2) and (4) include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert). The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 8: IV estimates of the effect of PM 2.5 on (log) respiratory ER visits, by age group

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
PM 2.5, same day (μg / m^3)	0.0012**	0.0022***	0.0012***	0.0017***	0.0029***
	[0.0006]	[0.0005]	[0.0004]	[0.0005]	[0.0005]
PM 2.5 × Alert	-0.0002	-0.0017***	-0.0009	-0.0018***	-0.0023***
	[0.0008]	[0.0006]	[0.0005]	[0.0007]	[0.0005]
Alert	-0.0215	-0.0680***	-0.0378**	-0.0602***	-0.0934***
	[0.0217]	[0.0195]	[0.0177]	[0.0211]	[0.0217]
Mean DV	3.452	9.313	8.076	16.415	2.936
Observations	351,325	351,325	351,325	351,325	351,325

Note: This table reports IV estimates of equation (1) by age group. The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. The instruments for $PM2.5$ are wind direction and speed and its interactions (see equation(2) for more details), and the instruments for $PM2.5 \times Alert$ are the same instruments interacted with $Alert$. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 9: Effect of PM 2.5 on different types of respiratory ER visits, by age group

	(1)	(2)	(3)	(4)	(5)
	< 1	1-4	5-14	15-64	65 +
Panel A: Total respiratory (J00-J99)					
PM 2.5, same day (μg / m^3)	0.0005***	0.0007***	0.0005***	0.0004***	0.0008***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Mean DV	3.176	8.824	7.914	15.835	2.827
R-squared	0.659	0.753	0.718	0.787	0.523
Observations	461,581	461,581	461,581	461,581	461,581
Panel B: Acute respiratory (J00-J21)					
PM 2.5, same day (μg / m^3)	0.0005***	0.0007***	0.0005***	0.0003***	0.0008***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Mean DV	2.616	7.547	6.883	13.523	2.078
R-squared	0.629	0.723	0.697	0.769	0.458
Observations	461,581	461,581	461,581	461,581	461,581
Panel C: Chronic respiratory (J40-J46)					
PM 2.5, same day (μg / m^3)	0.0000	0.0001	0.0000	0.0003***	0.0001
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Mean DV	0.287	0.560	0.284	0.643	0.386
R-squared	0.542	0.553	0.367	0.354	0.336
Observations	461,581	461,581	461,581	461,581	461,581
Panel D: Other respiratory					
PM 2.5, same day (μg / m^3)	0.0000	0.0002**	0.0000	0.0001	0.0002***
	[0.0000]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Mean DV	0.273	0.717	0.747	1.669	0.363
R-squared	0.456	0.571	0.558	0.577	0.345
Observations	461,581	461,581	461,581	461,581	461,581

Note: This table reports OLS estimates of equation (1) for different types of respiratory ER visits by age group. The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $*$ < .1, ** < .05, *** < .01.

Table 10: Effect of PM 2.5 on (log) respiratory ER visits by municipalities with different shares of residential wood burning emissions

	(1)	(2)	(3)	(4)	(5)
	< 1	1-4	5-14	15-64	65 +
Panel A: Share residential wood burning emissions less than 50 percent					
PM 2.5, same day (μg / m^3)	0.0003	0.0002	0.0002	0.0005***	0.0007**
	[0.0003]	[0.0003]	[0.0002]	[0.0002]	[0.0003]
Mean DV	2.845	7.757	6.499	12.460	2.265
R-squared	0.687	0.803	0.765	0.817	0.554
Observations	86,032	86,032	86,032	86,032	86,032
Panel B: Share residential wood burning emissions 50-75 percent					
PM 2.5, same day (μg / m^3)	0.0003*	0.0002	-0.0001	0.0001	0.0006***
	[0.0002]	[0.0002]	[0.0002]	[0.0002]	[0.0001]
Mean DV	3.512	9.392	8.363	16.971	2.921
R-squared	0.673	0.758	0.719	0.811	0.538
Observations	209,931	209,931	209,931	209,931	209,931
Panel C: Share residential wood burning emissions more than 75 percent					
PM 2.5, same day (μg / m^3)	0.0004***	0.0007***	0.0004***	0.0003**	0.0006***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0002]
Mean DV	2.963	8.716	8.117	16.245	3.002
R-squared	0.632	0.720	0.689	0.707	0.482
Observations	174,723	174,723	174,723	174,723	174,723

Note: This table reports OLS estimates of equation (1) in municipalities with different shares of residential wood burning emissions. The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $*$ < .1, ** < .05, *** < .01.

Table 11: Effect of PM 2.5 on (log) ER visits by different levels of air pollution

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
Panel A: Low average PM 2.5					
PM 2.5, same day (μg / m^3)	0.0002	0.0004	0.0003*	0.0007***	0.0007***
	[0.0001]	[0.0003]	[0.0002]	[0.0002]	[0.0002]
Mean DV	1.005	1.914	1.874	2.541	1.076
R-squared	0.577	0.667	0.654	0.695	0.451
Observations	145,895	145,895	145,895	145,895	145,895
Panel B: Intermediate average PM 2.5					
PM 2.5, same day (μg / m^3)	0.0008***	0.0009***	0.0005***	0.0003***	0.0012***
	[0.0001]	[0.0002]	[0.0001]	[0.0001]	[0.0001]
Mean DV	1.064	1.899	1.787	2.477	1.133
R-squared	0.723	0.835	0.805	0.866	0.584
Observations	157,238	157,238	157,238	157,238	157,238
Panel C: High average PM 2.5					
PM 2.5, same day (μg / m^3)	0.0004***	0.0006***	0.0004	0.0002	0.0005***
	[0.0001]	[0.0002]	[0.0002]	[0.0001]	[0.0002]
Mean DV	1.094	2.029	1.968	2.607	1.131
R-squared	0.657	0.717	0.661	0.746	0.528
Observations	167,553	167,553	167,553	167,553	167,553

Note: This table reports OLS estimates of equation (1) by different levels of air pollution. Low average PM 2.5 are hospitals with an average PM 2.5 (in 2013-2019) of 23 $\mu g/m^3$ or less; intermediate average PM 2.5 are hospitals with an average PM 2.5 between 23 and 30 $\mu g/m^3$; and high average PM 2.5 are hospitals with an average PM 2.5 of 30 $\mu g/m^3$ or more. The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 12: Effect of PM 2.5 on (log) respiratory ER visits. Robustness at municipality level.

	(1)	(2)	(3)	(4)	(5)	(6)
PM 2.5, same day (μg / m^3)	0.0006**	0.0007**	0.0002	0.0002	0.0000	0.0000
	[0.0003]	[0.0003]	[0.0002]	[0.0002]	[0.0001]	[0.0001]
Alert		-0.0101		0.0130		0.0262***
		[0.0273]		[0.0241]		[0.0083]
PM 2.5 × Alert		-0.0009**		-0.0004		-0.0001
		[0.0004]		[0.0003]		[0.0001]
Municipality FE	Yes	Yes	No	No	No	No
Municipality-Year FE	No	No	Yes	Yes	No	No
Municipality-Month-Year FE	No	No	No	No	Yes	Yes
Mean DV	18.442	18.442	18.442	18.442	18.442	18.442
R-squared	0.795	0.795	0.836	0.836	0.854	0.854
Observations	540,665	540,665	540,665	540,665	540,665	540,665

Note: This table reports OLS estimates of equation (1). The dependent variable is the logarithm of respiratory ER visits. All specifications include age group, hospital and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Columns (2), (4) and (6) include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 13: Effect of PM 2.5 on (log) respiratory ER visits, by age group. Robustness at municipality level.

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
PM 2.5, same day (μg / m^3)	0.0001	0.0000	-0.0000	0.0001	-0.0000
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Alert	0.0250**	0.0252**	0.0266*	0.0305**	0.0238
	[0.0104]	[0.0120]	[0.0141]	[0.0142]	[0.0149]
PM 2.5 × Alert	0.0001	-0.0002	-0.0001	-0.0001	-0.0003
	[0.0002]	[0.0002]	[0.0001]	[0.0002]	[0.0003]
Mean DV	7.834	21.851	19.090	37.012	6.424
R-squared	0.864	0.912	0.898	0.921	0.841
Observations	108,116	108,116	108,116	108,116	108,116

Note: This table reports OLS estimates of equation (1) by age group. The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and flexible controls for weather variables (daily maximum and minimum temperature and precipitation). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $*$ < .1, ** < .05, *** < .01.

Table 14: Effect of PM 2.5, CO and O3 on (log) respiratory ER visits

	(1)	(2)	(3)
PM 2.5 (μg / m^3)	0.0005**	0.0004**	0.0004**
	[0.0002]	[0.0002]	[0.0001]
CO (parts per billion)		0.0018	0.0016
		[0.0041]	[0.0040]
Ozone (parts per billion)			-0.0017
			[0.0011]
Mean DV	8.189	8.189	8.189
R-squared	0.814	0.814	0.814
Observations	1,038,260	1,038,260	1,038,260

Note: This table reports OLS estimates of equation (1) for different pollutants. The dependent variable is the logarithm of respiratory ER visits. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, ** < .05, *** < .01.

Table 15: Effect of PM 2.5 on (log) ER visits by different causes, by age group

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
Panel A: All respiratory					
PM 2.5, same day (μg / m^3)	0.0005***	0.0007***	0.0005***	0.0004***	0.0008***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Mean DV	3.261	9.069	8.058	16.161	2.908
R-squared	0.659	0.753	0.718	0.787	0.523
Observations	461,581	461,581	461,581	461,581	461,581
Panel B: Circulatory					
PM 2.5, same day (μg / m^3)	-0.0000	0.0000	-0.0000	0.0001*	0.0001
	[0.0000]	[0.0000]	[0.0000]	[0.0001]	[0.0001]
Mean DV	0.006	0.014	0.038	1.449	1.227
R-squared	0.109	0.130	0.158	0.595	0.667
Observations	461,581	461,581	461,581	461,581	461,581
Panel C: Traffic accidents					
PM 2.5, same day (μg / m^3)	-0.0000*	0.0000	-0.0000	-0.0001	0.0000
	[0.0000]	[0.0000]	[0.0000]	[0.0001]	[0.0000]
Mean DV	0.004	0.025	0.071	0.567	0.055
R-squared	0.087	0.349	0.438	0.700	0.362
Observations	461,581	461,581	461,581	461,581	461,581

Note: This table reports OLS estimates of equation (1) for different types of ER visits by age group. The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, ** < .05, *** < .01.

A Appendix: Online appendix not for publication

Table A.1: Effect of PM 2.5 on (log) respiratory ER visits. Robustness using a balance panel of monitors.

	(1)	(2)	(3)	(4)
PM 2.5, same day (μg / m^3)	0.0003**	0.0006***	0.0003***	0.0006***
	[0.0001]	[0.0002]	[0.0001]	[0.0001]
Alert		-0.0096		-0.0095*
		[0.0105]		[0.0054]
PM 2.5 × Alert		-0.0007***		-0.0005***
		[0.0002]		[0.0001]
Hospital-Month-Year FE	No	No	Yes	Yes
Mean DV	8.014	8.014	8.014	8.014
R-squared	0.525	0.525	0.549	0.549
Observations	1,792,180	1,792,180	1,792,180	1,792,180

Note: This table reports OLS estimates of equation (1). The sample drops monitors and hospitals that enter or exit in the period 2013-2019. The dependent variable is the logarithm of respiratory ER visits. All specifications include age group, hospital and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Columns (2) and (4) include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table A.2: Effect of PM 2.5 on (log) respiratory ER visits, by age group. Robustness using a balance panel of monitors.

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
PM 2.5, same day (μg / m^3)	0.0004***	0.0008***	0.0005***	0.0004***	0.0008***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Alert	0.0013	-0.0165**	-0.0106	-0.0083	-0.0135*
	[0.0077]	[0.0078]	[0.0080]	[0.0058]	[0.0072]
PM 2.5 × Alert	-0.0003**	-0.0005***	-0.0003**	-0.0003***	-0.0008***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0002]
Mean DV	3.532	9.483	8.189	15.903	2.962
R-squared	0.688	0.769	0.725	0.792	0.523
Observations	358,413	358,413	358,413	358,413	358,413

Note: This table reports OLS estimates of equation (1) by age group. The sample drops monitors and hospitals that entry or exit in the period 2013-2019. The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and controls for weather variables (daily maximum and minimum temperature and precipitation). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table A.3: Effect of PM 2.5 on (log) respiratory ER visits. Robustness with flexible weather controls.

	(1)	(2)	(3)	(4)
PM 2.5, same day (μg / m^3)	0.0002**	0.0004**	0.0002***	0.0004***
	[0.0001]	[0.0001]	[0.0000]	[0.0001]
Alert		-0.0025		-0.0039
		[0.0092]		[0.0047]
PM 2.5 × Alert		-0.0004**		-0.0003***
		[0.0002]		[0.0001]
Hospital-Month-Year FE	No	No	Yes	Yes
Mean DV	7.892	7.892	7.892	7.892
R-squared	0.551	0.551	0.575	0.575
Observations	2,307,865	2,307,865	2,307,865	2,307,865

Note: This table reports OLS estimates of equation (1). The dependent variable is the logarithm of respiratory ER visits. All specifications include age group, hospital and day-month-year fixed effects, and flexible controls for weather variables (daily maximum and minimum temperature and precipitation). Columns (2) and (4) include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table A.4: Effect of PM 2.5 on (log) respiratory ER visits, by age group. Robustness with flexible weather controls.

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
PM 2.5, same day (μg / m^3)	0.0003***	0.0004***	0.0002**	0.0003***	0.0006***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Alert	0.0042	-0.0068	-0.0013	-0.0044	-0.0111*
	[0.0066]	[0.0068]	[0.0074]	[0.0050]	[0.0066]
PM 2.5 $\times$ Alert	-0.0002	-0.0003**	-0.0001	-0.0003**	-0.0007***
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0002]
Mean DV	3.261	9.069	8.058	16.161	2.908
R-squared	0.660	0.754	0.719	0.787	0.524
Observations	461,523	461,523	461,523	461,523	461,523

Note: This table reports OLS estimates of equation (1) by age group. The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. All specifications include a dummy variable for air pollution alerts and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert), hospital-month-year and day-month-year fixed effects, and flexible controls for weather variables (daily maximum and minimum temperature and precipitation). Standard errors, clustered by monitor, are reported in brackets. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.