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

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May 31, 2022

Abstract

In this paper, we study the short-term effect of fine particulate matter (PM 2.5) exposure on respiratory Emergency Room (ER) visits in Chile, a middle-income country with high levels of air pollution. To instrument for PM 2.5 we use wind speed at different altitudes (pressure levels). Unlike previous papers, our data allow us to study the impact of increasing air pollution at high levels of pollution. We find that a 1 microgram per cubic meter ($\mu g/m^3$) increase in PM 2.5 exposure for one day increases ER visits for respiratory illness by 0.36 percent. The effect is positive for all age groups, including the middle-age population, a novel finding in the literature.

Keywords: Air Pollution, PM 2.5, Emergency Room Visits.

JEL codes: I12, I18, Q51, Q53

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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 short-term effect of PM 2.5 exposure on respiratory emergency room (ER) visits across the age distribution. We use data from Chile, a middle-income country with high levels of air pollution. In this line, the World Health Organization (WHO) emphasize the need to carefully examine the health impact of pollution in high contaminated economies since "extrapolation from studies in European and North American cities might not be applicable in countries with higher levels of exposure". (WHO (2016)).

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. Finally, variation in air pollution can be partially driven by human activity that can have itself a direct effect on health.

To overcome the threats to identification described above, we use air pollution data and a rich administrative dataset on ER visits covering all Chilean hospitals between 2013 and 2019. We have daily PM 2.5 measures from 86 monitors located across the country and daily information on total ER visits by age and cause of admission for all hospitals in the

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

country. Our unit of analysis is a hospital. Specifically, we match a hospital with monitors located within a 10 km distance. We use a sample of hospitals within a short distance from a monitor to obtain 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 an emergency episode. We then estimate the effect of PM 2.5 on ER visits using wind speed at different altitudes as instruments and ground-level wind speed as a control variable (along with other weather variables), and hospital-year fixed effects. Our key identifying assumption is that, once we control for ground-level wind speed, wind speed at different altitudes does not have a direct effect on ER visits (*exclusion restriction*) but may affect air pollution (*relevant condition*).

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 1 standard deviation change in PM 2.5 leads to a 3.6 percent increase in respiratory admissions for children aged 0-19 but no effect on the adult population. Gong et al. (2019) estimate the long-term effects 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. Godzinski and Castillo (2021) disentangle the effect of various air pollutants by using many instruments, and study their effect on emergency admissions and mortality in the largest urban areas in France. They find that PM 2.5 has a positive effect on cardiovascular-related mortality rate but no significant effects on respiratory ER admissions.

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 for all age groups. 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 microgram per cubic meter ($\mu g/m^3$) 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 air quality guideline[2] (10 $\mu g/m^3$ annual mean) was 98.6 percent in Chile; the same statistic in the US was 5.6 percent, and the mean in the OECD was 61.7 percent. Not only the annual mean but also the daily concentrations of PM 2.5 can get very high in Chile, reaching peaks of more than 100 $\mu g/m^3$ during several days through the winter months of the year. This is more than six times the WHO air quality recommendation of a 15 $\mu g/m^3$ 24-hour mean. Thus, in this paper, we identify the effects of pollution at levels not considered by the related papers.

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 decrease 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 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.

Our results at the hospital level indicate that a one $\mu g/m^3$ increase in PM 2.5 daily exposure increases ER visits for respiratory illness by 0.36 percent. When we aggregate the data at the county level (as is usual in the literature), the results are equally significant but smaller in magnitude, with a 0.17 percent increase in respiratory ER visits. Nevertheless, this effect is 2.5 times larger than the same effect for the US reported in recent literature (see, for example, Deryugina et al., 2019).

We also find that all age groups are affected. In particular, we find that for the

[2]This OECD indicator corresponds to the 2005 WHO air quality guideline of an annual mean of 10 $\mu g/m^3$. This target changed to an annual mean of 5 $\mu g/m^3$ in 2021.

middle-aged group, between 15-64 years old, an increase of 1 $\mu g/m^3$ in PM 2.5 increases respiratory ER visits by 0.32 percent. As the middle-aged population constitutes the largest group, any positive effect on ER visits may have important repercussions on the whole health system. This is a new result in the literature. Papers that study the effect of PM 2.5 on ER visits or admissions consider only selected age groups (Deryugina et al. (2019)) or find an impact only for some age groups (Godzinski and Castillo (2021)). A noteworthy exception is Gong et al. (2019), who find a positive effect of PM 2.5 on mortality rate using data for China. Note that, similar to Chile, China has a much higher level of pollution than those studied in other related papers, which could explain why they also find an effect for the middle-aged group.

Finally, we also explore the effect on respiratory 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. When we explore the effects by geographical region, we find that the effect of pollution is concentrated in different age groups depending on the geographic location, which may be related to the different sources of emissions that are prevalent in the different regions. Finally, we also study the robustness of our results by controlling for pollution alerts, for lags in the pollution variables, and by performing the analysis at the municipality level.

Our paper is organized as follows. Section 2 describes the data. Section 3 presents the empirical model. Section 4 discusses the results. Wee run a series of robustness checks in 5 and conclude in Section 6.

2 Data

Air pollution

We obtain air pollution data from the Air Quality National Information System (SINCA) of the Chilean Ministry of Environmental Affairs.[3] 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 have daily PM 2.5 information from 86 monitors during the period 2013-2019. The monitors are located in representative areas

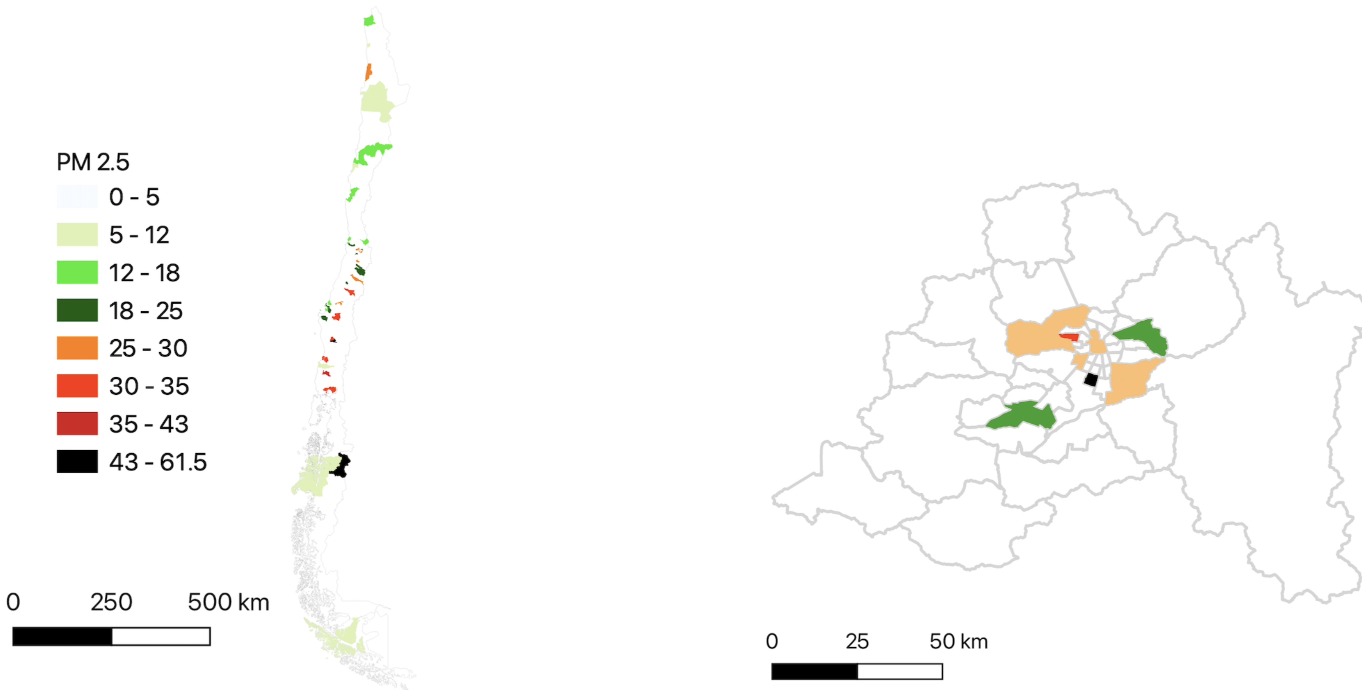
[3]Sistema de Informacion Nacional de Calidad del Aire.

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 industrial 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 with PM are in the central part (Santiago Metropolitan Area and Valparaíso) and the south part of the country.

(a) All Monitors

(b) Monitors in Santiago Metropolitan Area

Figure 1: Geographic distribution of Monitors



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

Figure 2: Average PM 2.5 by municipality, 2013-2019

To further understand the differences in pollution across regions in Chile, Figure 3 shows PM 2.5 emission share by source and region (ordered from north to south) in 2018-2019.[4] In the northern part of the country, the most important emission sources are road transport and stationary sources such as fossil fuel burning power plants, mainly related to mining activities.[5] The most important emission source in the southern part of the country is the residential burning of wood. Finally, in the central area of the country, Santiago Metropolitan Area and Valparaíso, emissions come mainly from road transport and residential burning of wood.

Atmospheric Conditions

We use two types of data on atmospheric conditions: ground-level weather data and altitude-weather data.

[4]Data on emission sources by region in 2018-2019 is from the *Registro de Emisiones y Transferencias Contaminantes* (RETC).

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

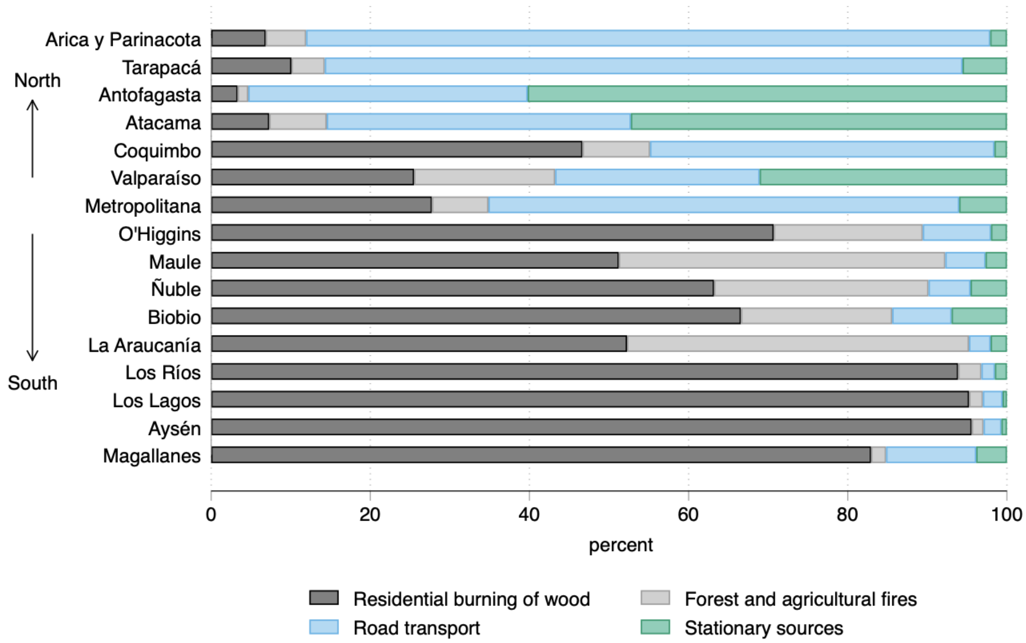


Figure 3: PM 2.5 emission share by source and region, 2018-2019

Ground-level weather data comes from the Center for Climate and Resilience Research (temperature and precipitation) and SINCA (wind speed). The Center for Climate and Resilience Research 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*. There are in total 295 stations reporting hourly temperature and 816 stations reporting hourly precipitations. We use the hourly data to compute the daily maximum and minimum temperature, and the daily cumulative precipitation.[6] We complement these data with wind information from 127 SINCA stations. SINCA stations report hourly information on wind speed (in km/hour). We average the hourly wind speed to compute the daily wind speed.

Altitude-weather data comes from NASA's Modern-Era Retrospective analysis for

[6]The data on atmospheric conditions are publicly available from http://www.cr2.cl/recursos-y-publicaciones/bases-de-datos. We keep stations with more than 2 years of data. We drop daily observations with minimum temperatures below -30 degrees Celsius or above 35 degrees Celsius, maximum temperatures below -25 degrees Celsius or above 42 degrees Celsius, or negative values of precipitation. We also drop observations where the maximum temperature is more than 3 SD above or below the mean maximum temperature in that month of the year, and we did the same for minimum temperatures.

Research and Applications, Version 2 (MERRA-2).[7] MERRA-2 is a reanalysis data product that combines observations from various sources with an atmospheric data assimilation algorithm to produce a 3-dimensional, gridded dataset containing atmospheric conditions for all the planet since 1980. MERRA-2 data is provided with a spatial resolution of 5/8° longitude by 1/2° latitude grid at 6 different times (00 GMT, 06 GMT, 12 GMT, and 18 GMT). We obtained east-west wind direction (u-component) and north-south wind direction (v-component) at different atmospheric pressure levels from the M2I6NPANA file. These data are available for 42 atmospheric pressure levels (layers), corresponding to different altitudes. We download these data for those locations where there exist SINCA monitors measuring either MP 2.5 or wind speed to minimize the computational burden of downloading the data for the whole country. Finally, for each layer, we convert the average u- and v-component into wind speed and then average wind speed at the daily level.

Emergency department visits

We obtain data on ER visits from Chile's Ministry of Health.[8] The dataset includes all daily ER visits in Chile for the period 2013–2019 by cause, age group, and hospital. Age groups are 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 subgroups 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 10 km radius of a monitor as our unit of observation. Using information from SINCA monitors within a 10 km radius of a hospital, we use inverse distance weighting to compute PM 2.5 at the hospital location. We then average maximum and minimum temperatures from stations within 50 km from the hospital, and precipitation and wind speed (both ground-level and altitude-weather level) from weather stations within 20 km from the hospital. By restricting our sample to hospitals within a short distance of a monitor, we have a more accurate

[7] See Gelaro et al. (2017) for a description of MERRA-2 and Bosilovich et al. (2016) for detailed information on the available data.

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

measurement of air pollution near the hospital. If people 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.

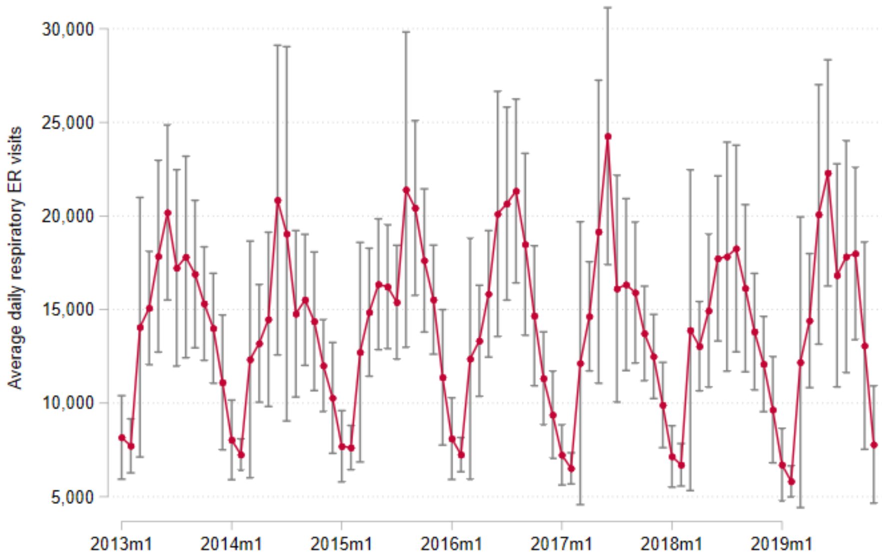
Table 1 shows the number of hospitals and observations in our sample by year. Since the the number of monitors has increased over time, the number of hospitals we can match to a monitor has increased, as well.[9]

Table 2 shows summary statistics of our sample. We have 2,618,765 observations. The average concentration of PM 2.5 is 26.32. The average number of daily ER visits per hospital is 27, and around 30 percent of these ER visits correspond to respiratory conditions. From those, 77 percent correspond to acute respiratory conditions. The average maximum temperature is 21 degrees Celsius; the average minimum temperature is 9 degrees Celsius; the average precipitation is 1.22 mm; and the average ground level wind speed is 1.63 km per hour. As expected wind speed at altitude increases with altitude.

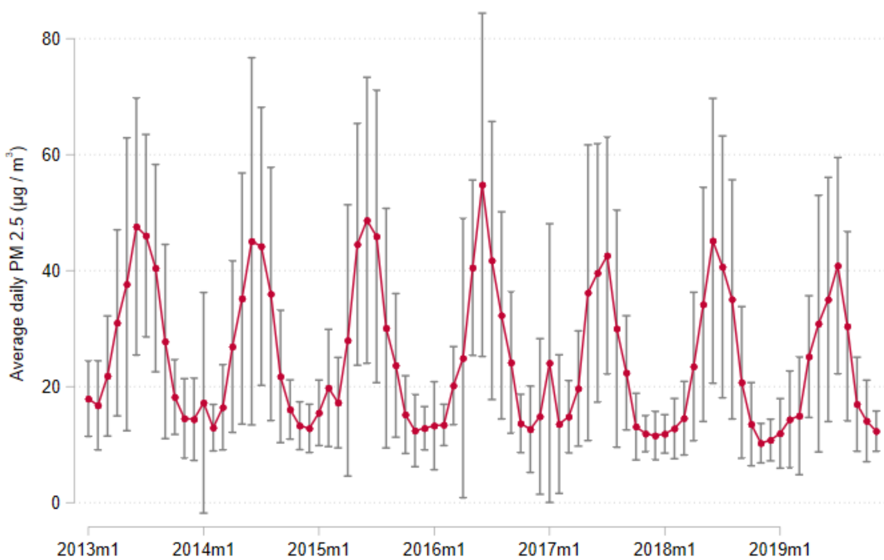
Figure 4 shows the average daily respiratory ER visits (panel (a)) and the average daily PM 2.5 (panel (b)). Note that both variables are highly seasonal and highly correlated with each other. Note also that both pollution and respiratory ER visits are higher during the winter (June-August). Figure 5 shows the average daily mean across regions. The central and southern regions show higher levels of pollution, reaching a daily mean close to 60 $\mu g/m^3$. Note, however, that even during the summer, when pollution is lower, the daily mean is higher than the WHO air quality recommendation for PM 2.5, which is an annual average daily mean of 5 $\mu g/m^3$ and a 24 hours-concentration of 15 $\mu g/m^3$. So, PM 2.5 is above what is considered healthy for most of the year across regions.

Finally, Table 3 shows the overall variation in PM 2.5 and further decomposed in the between hospital-year-month and the within hospital-year-month variation. As observed from the table, the within-variation is similar to 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.

[9] In Section 5, we confirm that our results are not driven by entry/exit of hospitals. We estimate our main model with a balanced sample and find similar results.



(a) Respiratory ER visits



(b) Average daily PM 2.5 concentration

Figure 4: Air pollution and respiratory ER visits, 2013-2019

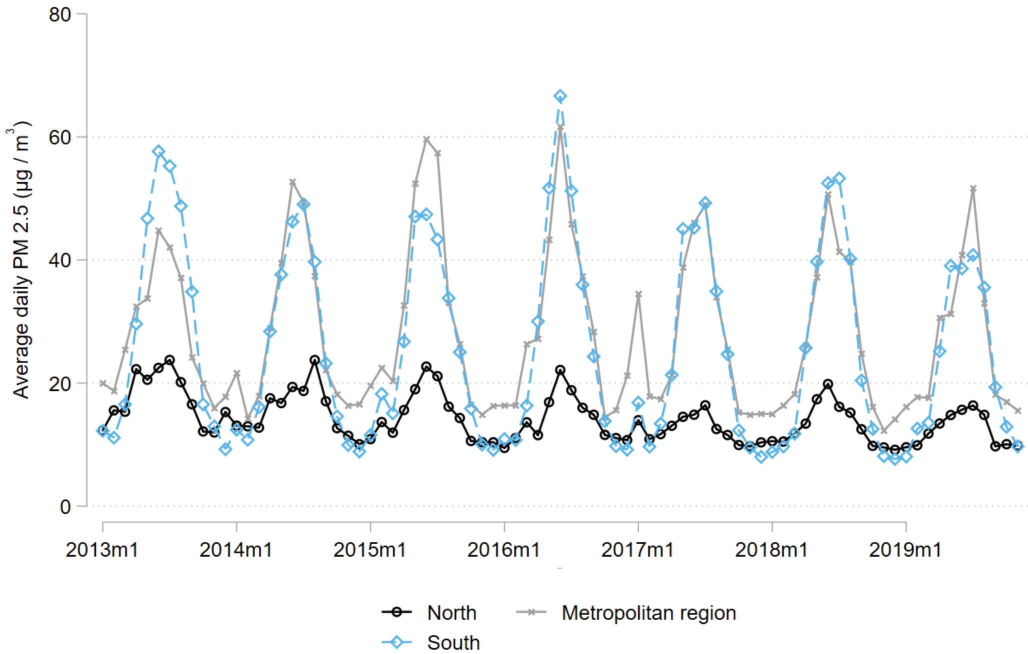


Figure 5: Average daily PM 2.5 concentration by region

3 Empirical Strategy

We estimate the short-term effect of PM 2.5 exposure on respiratory ER visits using the following model:

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

where Y_{hadmy} is the logarithm of respiratory ER visits for age group a in hospital h on day d in month m and year y; $PM2.5_{hdmy}$ is the PM2.5 in hospital h on dmy; X_{hdmy} are weather variables (daily max and min temperature and precipitation) in hospital h on dmy; α_a is an age group fixed effect; α_{hy} is an hospital-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.

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-year cell is not as good as randomly assigned. There could be measurement error in exposure to PM 2.5 because our daily measures of PM 2.5 levels at the monitor location could differ from the actual exposure of individuals who visit the ER. To minimize this source of measurement error, we choose hospitals located within a 10 km radius from a monitor. Because we focus on emergency episodes, we expect that the place of residence or work should be a short distance from the hospital.

Given the possible endogeneity of the allocation of PM 2.5 within a hospital-year cell, we use wind speed at different altitudes to instrument the level of PM 2.5, using ground-level wind speed as a control variable. As described above, we have data for atmospheric conditions for a vertical grid parametrizing altitude through 42 different pressure levels (layers). The layers start at 1000 hPa (approximately 100 meters above sea level) and end at 0.1 hPa (approximately 37,000 meters above sea level). We choose only 3 layers to minimize problems with many instruments: 12 (725 hPa), 16 (550 hPa), and 18 (450 hPa).[10] We start with layer 12 at 725 hPa (approximately 2,500 meters) because there were several missing values for the layers below layer 12 (the average altitude in Chile is 1,800 meters) and also to avoid potential collinearity with ground-level wind speed.[11]

Our instrument satisfies the exclusion restriction because we use ground-level wind speed as a control variable to capture the direct effect that wind speed may have on health. Therefore, wind speed at different altitudes is unlikely to have a direct effect on ER visits and may only affect health through the level of pollution. 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

$$\begin{aligned} PM2.5_{hdmy} =& \pi_1 wind\,speed^{12}_{hdmy} + \pi_2 wind\,speed^{16}_{hdmy} + \pi_3 wind\,speed^{18}_{hdmy} \\ &+ X'_{hdmy}\theta + \alpha_a + \alpha_{hmy} + \alpha_{dmy} + \epsilon_{hadmy}, \end{aligned} \tag{2}$$

where $wind\,speed^{12}_{hdmy}$, $wind\,speed^{16}_{hdmy}$ and $wind\,speed^{18}_{hdmy}$are the average daily wind speed in hospital h on date dmy measured at three different pressure levels: $725hPa$ (layer 12), $550hPa$ (layer 16), and $450hPa$ (layer 18).

We estimate equations (1) and (2) clustering the standard errors at the hospital level.

[10]When we estimate the model with all the layers between 12 and 18, we find similar results.
[11]Other papers using similar instruments are, for example, Schwartz et al. (2017) or Godzinski and Castillo (2021).

4 Results

Table 4 shows the OLS (columns (1) and (2)) and IV (columns (3) and (4)) estimates of the impact of PM 2.5 on respiratory ER visits. Columns (1) and (3) in the table show a basic specification with hospital fixed effects, and columns (2) and (4) show our preferred specification, which includes hospital-year interactions. We estimate that an increase in 1 $\mu g/m^3$ in PM 2.5 increases respiratory ER visits from 0.32 to 0.36 percentage points. These results are twelve times larger than the OLS estimates.[12] The estimated effect is not negligible: a 1 standard deviation increase in PM 2.5 (around 24 $\mu g/m^3$) increases respiratory ER visits by 8 percentage points. The test of weak instruments in the first stage has an F-stat of 272.9, showing that the instruments satisfy the relevance condition necessary for identification in the IV estimation.

Using our preferred specification, which includes hospital-year interactions, we explore heterogeneous effects by age group in Figure 6 and Table 5. An increase in PM 2.5 causes an increase in respiratory ER visits in all age groups, including the 15-64 years-old population. Coefficients across age groups are close enough to be statistically indistinguishable. In particular, we find that for the 15-64 age group, a 1 $\mu g/m^3$ increase in PM 2.5 leads to a 0.32 percent increase in respiratory ER visits. The last result is important. The middle-aged population constitutes the largest group, so any positive effect on respiratory ER visits also has a potentially large impact on the health system. A plausible explanation is that, at higher levels of pollution, every age group is affected by higher concentration of PM. 2.5.

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

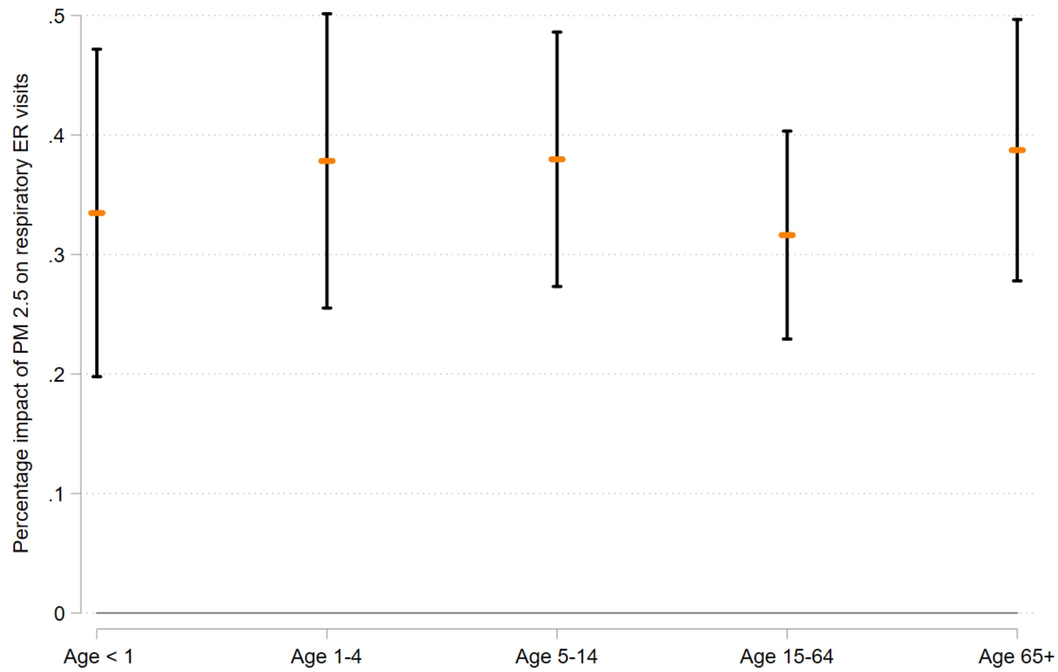


Figure 6: IV estimates of the effect of PM 2.5 on (log) respiratory ER visits, by age group

Table 6 explores the effect of PM 2.5 on different types of 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 affected by daily variations on pollution only for people older than 65 (and marginally for children aged 5-14) and not for the other age groups (Panel C).

Given the difference between pollution levels in different parts of the country, in Table 7 and Figure 7, we show the results when we divide our national sample into three geographical regions (North, South, and Santiago Metropolitan). In the North region we find a positive and significant effect for the population between 1-4 and 15-64 years old. The difference in the results by geographical region may be related to the heterogeneity in sources of pollution (see Figure 3 on page 8). Notice than, for example, in the North, where mining activities are important, we only observe impacts in older children and adults, but not in elderly people or young children. However, in the Santiago Metropolitan area, where road transport is the dominant source, the effect are concentrated in young children (age 0-5). Finally, notice that in the South, where the main source of pollution is residential wood

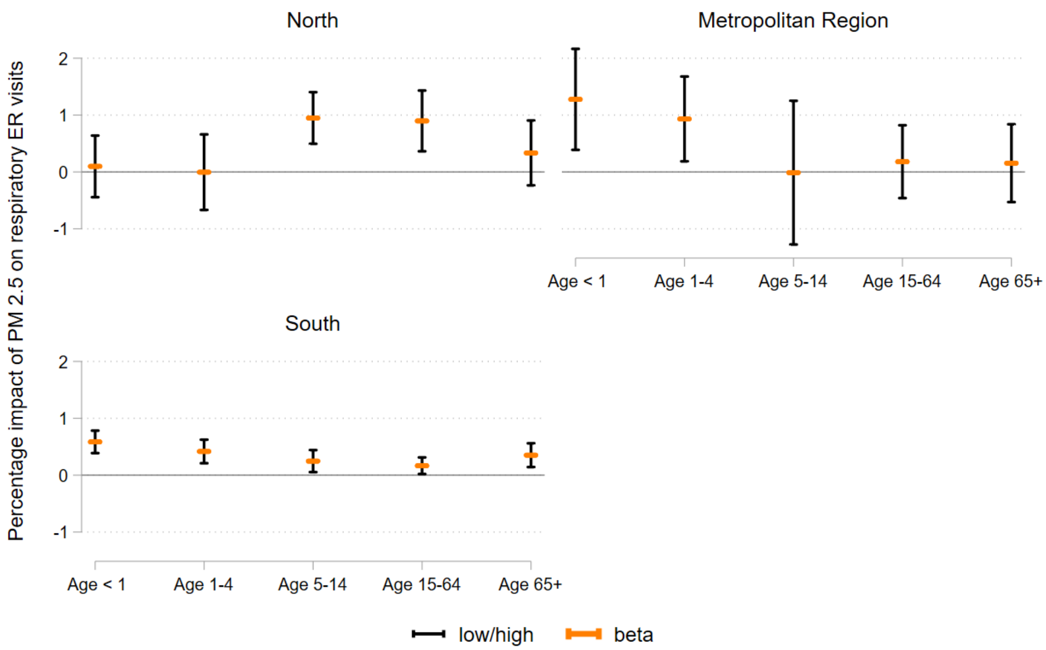


Figure 7: IV estimates of the effect of PM 2.5 on (log) respiratory ER visits by region

burning and the average pollution level is the highest, we observe effects for all age groups, even though they are lower than in the other cases.

5 Robustness Checks

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

First, we control for alerts as they may cause avoidance behavior (Neidell (2009); Moretti and Neidell (2011)), or change the pollution level by triggering mitigation actions (Rivera (2021). Data on air quality episodes are obtained from the *Ministry of Environmental Affairs*. This system is used in thirteen different geographical areas located in the Santiago Metropolitan Area and the south of Chile during winter.[13]

The issuance of air quality episodes is based on a forecasting model of PM 2.5 for the following day. When the forecasted PM 2.5 is equal to or higher than $80\mu g/m^3$ in at least one of the monitors located in a geographic area, the environmental authority recommends to the

[13]The system 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 was 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.

local government issue an *air quality episode* for the following day. Depending on the severity of the pollution, there are three different types of air quality episodes. An alert episode is issued when PM 2.5 is expected to be between 80 and 109 $\mu g/m^3$; a pre-emergency episode is issued when PM 2.5 is expected to be between 110 and 169 $\mu g/m^3$, and an emergency episode is issued when PM 2.5 is expected to be higher than 170 $\mu g/m^3$. These episodes trigger protocols, such as driving restrictions, prohibition of residential wood combustion, the shutdown of stationary pollution emission sources, and cancellation of physical exercise classes for elementary and high school students. The specific mitigation actions depend on each geographical area. We construct the variable $Alert$, a dummy that indicates if a PM 2.5 episode of alert, pre-emergency, or emergency is issued on a given day in a monitor's location. Table 8 show the results. First, notice that the main coefficient is similar to the one in the main specification in the OLS specification and slightly higher in the IV specification. Both the dummy and its interaction with PM 2.5 have a negative effect on respiratory ER visits. The negative sign for the interaction effect indicates that respiratory ER visits decrease when pollution level increases and an alert is issued. This results is in line with Kim (2021), who also finds a negative interaction effect. However, we find a negative direct effect of alerts on ER visits, suggesting the presence of avoidance behavior.

Second, in our empirical specification, we match hospitals to monitors within a 10 km distance to have a more accurate measure of pollution exposure. However, most of the previous literature studies the impact of pollution at the county level. Therefore, to facilitate the comparison of our results, we estimate our preferred specification at this level with the respiratory ER visit rate per million residents as the dependent variable. Tables 9 and 10 show the results of this exercise. In Table 9, we find that an increase in 1 $\mu g/m^3$ in PM 2.5 increases respiratory ER visits by 4.48 per million (0.16 percentage points), sizably lower than those in our main specification (0.36 percentage points). However, we find a larger impact than Deryugina et al. (2019), who find that an increase of 1 $\mu g/m^3$ in PM 2.5 increases ER visits by 2.69 per million people in the US (0.07 percentage points). To make the comparison more accurate we should focus on people aged 65 and over, (Table 10) where we find an increase of 4.97 visits per million people, making the difference even larger. This difference might be due to the higher level of the overall pollution in our data, which leads to bigger effects. Table 10 confirms that, with this alternative specification, we find a significant impact for all ages. In the online appendix, we repeat this analysis with the logarithm of respiratory ER visits as the dependent variable, with similar results.

Third, we run some falsification tests using non-respiratory ER visits that are less likely to be affected by air pollution. Table 11 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.

Fourth, we also study the cumulative effects of pollution. Table 12 shows the results when we add two lags of the PM 2.5 variable. The main result remains robust and the lags do not seem significant to explain respiratory ER on the same day. Table 13 shows the results when we use 3-day average PM 2.5 as the measure for pollution. The main result remains robust although lower in magnitude.

Finally, in Tables A.4 and A.5 in the Online Appendix, we show that our results are robust to using a balanced panel of hospitals (dropping those hospitals that enter the sample due to the entry of new monitors). They are also robust to using weights for each hospital equal to the annual average number of respiratory ER visits for each age group.

Figure 8 summarizes the results for the different specifications described above and those in the online Appendix. The effects show that an increase of $1\mu g/m^3$ in PM 2.5 increases respiratory ER visits between a range from .18 to .42, depending on the specification. These effects are, however, higher than in the related literature.

6 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, 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

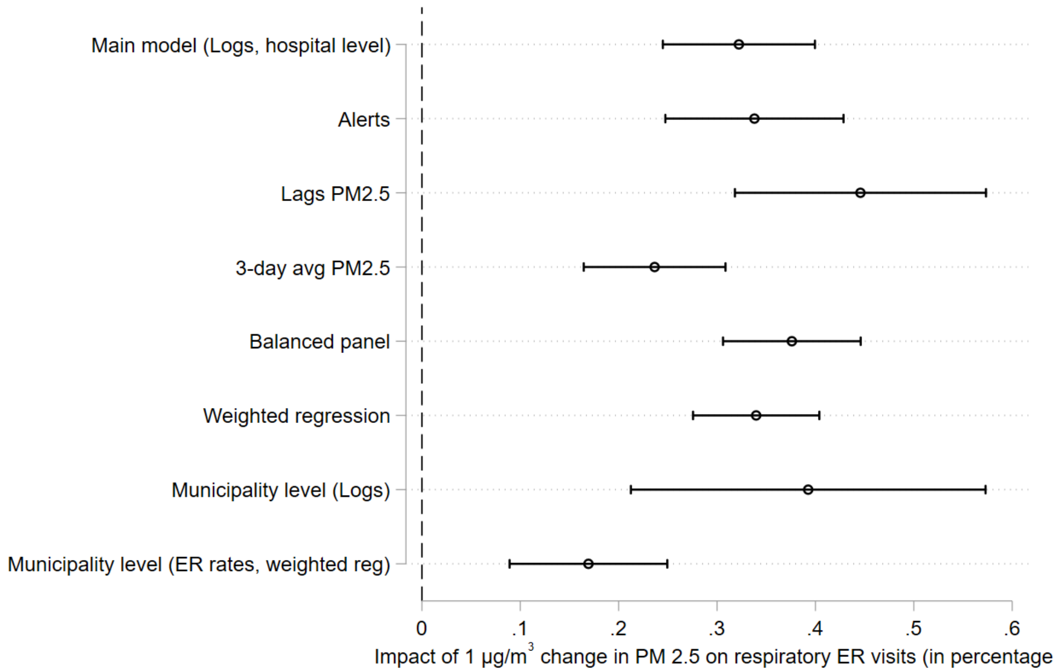


Figure 8: Effect of PM 2.5 on respiratory ER visits. Different specifications.

literature: sorting of individuals, seasonal factors, measurement error due to the unknown true exposure level and avoidance behavior, and endogeneity of air pollution. Our identification strategy uses wind speed at different altitudes to instrument the level of PM 2.5, using ground-level wind speed as a control variable. instrument air pollution using altitude wind speed. Our instrument satisfies the exclusion restriction because we use ground-level wind speed as a control variable to capture the direct effect that wind speed may have on health. Therefore, wind speed at different altitudes is unlikely to have a direct effect on ER visits and may only affect health through the level of pollution. Moreover, because the level of fine particulates depends on weather conditions such as wind, our instrument is correlated with air pollution.

We find that an increase of 1 $\mu g/m^3$ in PM 2.5 increases respiratory ER visits from 0.32 to 0.36 percentage points, a bigger effect than previous work on less polluted countries. Moreover, we find similar effects for all age groups. In particular, the 14-65 years old groups are similarly affected by air pollution than other, more sensitive groups like children and older adults (65+).

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Appendix: Tables

Table 1: Number of hospitals by year

Year	Number of Hospitals	Number of Observations
2013	204	327,740
2014	209	357,565
2015	222	367,425
2016	240	392,815
2017	240	413,685
2018	242	411,715
2019	244	347,820

Note: This table reports the number of hopitals and observations by year for the estimation sample.

Table 2: Summary statistics, 2013–2019

Variables	Mean	s.d.
Pollution		
PM 2.5 (μg / m^3)	26.32	22.77
Respiratory	8.16	9.85
Acute respiratory (J00-J21)	6.81	8.64
Chronic respiratory (J40-J46)	0.44	1.22
Other respiratory	0.91	3.05
Circulatory	0.55	1.69
Traffic accidents	0.14	1.15
Weather		
Max. Daily Temp. (Celsius)	20.92	6.36
Min. Daily Temp. (Celsius)	8.96	4.07
Daily precipitation (mm)	1.22	4.96
Wind Speed (km/hour)	1.63	0.90
Wind Speed (layer 12) (km/hour)	7.97	4.96
Wind Speed (layer 16) (km/hour)	14.60	7.00
Wind Speed (layer 20) (km/hour)	26.46	11.67
Observations	2,618,765	

Note: This table reports descriptive statistics for the estimation sample. Unit of observation is hospital-day. Altitude wind speed is measured at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18).

Table 3: 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	26.32	22.77	0.00	739.35	523,753
	between	.	16.74	0.00	376.55	17,798
	within	.	15.77	-144.91	723.62	29

Note: This table reports the variation in PM 2.5 for the estimation sample. The "between" variation is the variation across hospital-month-year, and the "within" variation is the variation within a hospital-month-year. N is total number of hospital-year-month-day observations (overall variation), n is the total number of hospital-year-month observations (between variation) and Tbar is the average number of observations by a hospital in a month (within variation).

Table 4: 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 (μg / m^3)	0.0002***	0.0002***	0.0032***	0.0036***
	[0.0001]	[0.0001]	[0.0004]	[0.0003]
Hospital FE	Yes	No	Yes	No
Hospital-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)			304.5	272.9
p-value PM 2.5 (weak inst.)			0.000	0.000
Mean DV	8.165	8.165	8.165	8.165
Observations	2,618,765	2,618,765	2,618,765	2,618,765

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 speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include hospital, day-month-year and age group fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 5: 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 (μg / m^3)	0.0033***	0.0038***	0.0038***	0.0032***	0.0039***
	[0.0007]	[0.0006]	[0.0005]	[0.0004]	[0.0006]
Mean DV	3.236	9.043	8.248	17.335	2.962
Observations	523,637	523,637	523,637	523,637	523,637

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 speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include hospital-month and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table 6: IV estimates of the effect of PM 2.5 on different types of respiratory ER visits, by age group

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
Panel A: All respiratory (J00-J99)					
PM 2.5 (μg / m^3)	0.0033***	0.0038***	0.0038***	0.0032***	0.0039***
	[0.0007]	[0.0006]	[0.0005]	[0.0004]	[0.0006]
Mean DV	3.236	9.043	8.248	17.335	2.962
Observations	523,637	523,637	523,637	523,637	523,637
Panel B: Acute respiratory (J00-J21)					
PM 2.5 (μg / m^3)	0.0032***	0.0037***	0.0037***	0.0031***	0.0038***
	[0.0007]	[0.0006]	[0.0006]	[0.0005]	[0.0006]
Mean DV	2.652	7.654	7.061	14.502	2.165
Observations	523,637	523,637	523,637	523,637	523,637
Panel C: Chronic respiratory (J40-J46)					
PM 2.5 (μg / m^3)	0.0003	-0.0002	0.0006*	0.0007	0.0011***
	[0.0004]	[0.0005]	[0.0003]	[0.0005]	[0.0004]
Mean DV	0.291	0.566	0.288	0.679	0.400
Observations	523,637	523,637	523,637	523,637	523,637
Panel D: Other respiratory					
PM 2.5 (μg / m^3)	0.0004	0.0005	0.0005	0.0003	0.0005
	[0.0003]	[0.0004]	[0.0006]	[0.0006]	[0.0003]
Mean DV	0.294	0.822	0.900	2.154	0.398
Observations	523,637	523,637	523,637	523,637	523,637

Note: This table reports IV 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. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include hospital and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

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

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
Panel A: North					
PM 2.5 (μg / m^3)	0.0010	-0.0000	0.0095***	0.0090***	0.0033
	[0.0028]	[0.0034]	[0.0023]	[0.0027]	[0.0029]
F stat PM 2.5 (weak inst.)	716.3	716.3	716.3	716.3	716.3
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	1.036	1.864	1.834	2.512	0.999
Observations	49,225	49,225	49,225	49,225	49,225
Panel B: Metropolitan region					
PM 2.5 (μg / m^3)	0.0128***	0.0093**	-0.0001	0.0018	0.0015
	[0.0045]	[0.0038]	[0.0064]	[0.0033]	[0.0035]
F stat PM 2.5 (weak inst.)	210.9	210.9	210.9	210.9	210.9
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	1.050	1.950	1.883	2.628	1.129
Observations	284,163	284,163	284,163	284,163	284,163
Panel C: South					
PM 2.5 (μg / m^3)	0.0059***	0.0042***	0.0025**	0.0017**	0.0035***
	[0.0010]	[0.0011]	[0.0010]	[0.0007]	[0.0011]
F stat PM 2.5 (weak inst.)	55.0	55.0	55.0	55.0	55.0
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	1.078	1.987	1.944	2.629	1.163
Observations	190,126	190,126	190,126	190,126	190,126

Note: This table reports OLS and IV estimates of equation (1) by different regions by age group. North includes regions located to the north of the Metropolitan region; South includes regions located to the south of the Metropolitan region. The dependent variable is the logarithm of respiratory ER visits. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include hospital, day-month-year and age group fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 8: OLS and IV estimates of the effect of PM 2.5 on (log) respiratory ER visits. Robustness controlling for pollution alerts.

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5 (μg / m^3)	0.0002***	0.0002***	0.0036***	0.0038***
	[0.0001]	[0.0001]	[0.0003]	[0.0004]
Alert		0.0174***		-0.0702***
		[0.0063]		[0.0240]
PM 2.5 × Alert		-0.0003***		-0.0023**
		[0.0001]		[0.0010]
Hospital-Year FE	Yes	Yes	Yes	Yes
F stat PM 2.5 (weak inst.)			272.9	286.5
p-value PM 2.5 (weak inst.)			0.000	0.000
F stat PM 2.5 × Alert (weak inst.)				58.4
p-value PM 2.5 × Alert (weak inst.)				0.000
Mean DV	8.165	8.165	8.165	8.165
Observations	2,618,765	2,618,765	2,618,765	2,618,765

Note: This table reports OLS and IV estimates of equation (1) controlling for pollution alerts. The dependent variable is the logarithm of respiratory ER visits. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). Columns (2) and (4) include a dummy variable for an air pollution alert and its interaction with $PM2.5$ (in deviations with respect to 80 $\mu g/m^3$, the PM level that activates the alert). All specifications include hospital, day-month-year and age group fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 9: IV estimates of the effect of PM 2.5 on respiratory ER rates at municipality level. Weighted regression.

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5, same day (μg / m^3)	0.641**	0.488*	4.457***	4.485***
	[0.317]	[0.277]	[1.143]	[1.084]
Municipality FE	Yes	No	Yes	No
Municipality-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)			26.3	29.5
p-value PM 2.5 (weak inst.)			0.000	0.000
Mean DV	2,650	2,650	2,650	2,650
Observations	345,820	345,820	345,820	345,820

Note: This table reports IV estimates of equation (1) at the municipality level. The dependent variable is the respiratory ER visit rate per million of residents in the relevant age group. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include hospital, day-month-year and age group fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. Estimates are weighted by the number of residents in the relevant age group. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table 10: IV estimates of the effect of PM 2.5 on respiratory ER rates at municipality level, by age group. Weighted regression.

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
PM 2.5, same day (μg / m^3)	31.612**	22.455***	8.285***	1.947***	4.974***
	[12.854]	[6.755]	[2.902]	[0.639]	[1.059]
Mean DV	6,312	4,118	1,512	606	700
Observations	68,761	68,761	68,761	68,761	68,761

Note: This table reports IV estimates of equation (1) by age group at the municipality level. The dependent variable is the respiratory ER visit rate per million of residents in the relevant age group. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include municipality and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. Estimates are weighted by the number of residents in the relevant age group. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by municipality, are reported in brackets. Significance levels are indicated by $* < .1$, ** < .05, *** < .01.

Table 11: IV estimates of the effect of PM 2.5 on (log) ER visits by ER type

	(1) Respiratory	(2) Circulatory	(3) Traffic accidents
PM 2.5 (μg / m^3)	0.0036***	-0.0000	0.0001
	[0.0003]	[0.0001]	[0.0001]
F stat PM 2.5 (weak inst.)	272.9	272.9	272.9
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000
Mean DV	8.165	0.551	0.144
Observations	2,618,765	2,618,765	2,618,765

Note: This table reports IV estimates of equation (1) for different types of ER visits. The dependent variable is the logarithm of ER visits for the corresponding ER type. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include hospital-month and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, ** < .05, *** < .01.

Table 12: OLS and IV estimates of the effect of PM 2.5 on (log) respiratory ER visits using two lags of PM 2.5.

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5, same day (μg / m^3)	0.0001	0.0001*	0.0044***	0.0045***
	[0.0001]	[0.0001]	[0.0007]	[0.0007]
PM 2.5, 1-day lag (μg / m^3)	0.0001**	0.0001	-0.0019*	-0.0014
	[0.0001]	[0.0001]	[0.0010]	[0.0010]
PM 2.5, 2-day lag (μg / m^3)	0.0001	0.0001	-0.0006	-0.0006
	[0.0001]	[0.0001]	[0.0008]	[0.0008]
Hospital FE	Yes	No	Yes	No
Hospital-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)			116.9	114.3
p-value PM 2.5 (weak inst.)			0.000	0.000
Mean DV	8.165	8.165	8.165	8.165
Observations	2,168,715	2,168,715	2,168,715	2,168,715

Note: This table reports OLS and IV estimates of equation (1) that include two lags of $PM2.5$. The dependent variable is the logarithm of respiratory ER visits. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). Lagged $PM2.5$ are isntrumented using lagged instruments. All specifications include hospital, day-month-year and age group fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 13: OLS and IV estimates of the effect of PM 2.5 on (log) respiratory ER visits using 3-day average PM 2.5.

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5 3-day avg. (μg / m^3)	0.0003**	0.0003***	0.0020***	0.0024***
	[0.0001]	[0.0001]	[0.0005]	[0.0004]
Hospital FE	Yes	No	Yes	No
Hospital-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)			228.7	183.8
p-value PM 2.5 (weak inst.)			0.000	0.000
Mean DV	8.165	8.165	8.165	8.165
Observations	2,568,250	2,568,250	2,568,250	2,568,250

Note: This table reports OLS and IV estimates of equation (1) using 3-day average $PM2.5$. The dependent variable is the logarithm of respiratory ER visits. The instruments for 3-day average $PM2.5$ are 3-day average wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include hospital, day-month-year and age group fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

A Appendix: Online appendix not for publication

Table A.1: IV estimates of the effect of PM 2.5 on (log) respiratory ER visits at municipality level.

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5, same day (μg / m^3)	0.0003**	0.0001	0.0039***	0.0039***
	[0.0001]	[0.0001]	[0.0009]	[0.0009]
Municipality FE	Yes	No	Yes	No
Municipality-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)			33.8	29.2
p-value PM 2.5 (weak inst.)			0.000	0.000
Mean DV	32.078	32.078	32.078	32.078
Observations	345,820	345,820	345,820	345,820

Note: This table reports IV estimates of equation (1) at the municipality level. The dependent variable is the logarithm of respiratory ER visits. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include municipality and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by municipality, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table A.2: IV estimates of the effect of PM 2.5 on (log) respiratory ER visits at municipality level. Weighted regression.

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5, same day (μg / m^3)	0.0003	-0.0001	0.0025***	0.0025***
	[0.0003]	[0.0001]	[0.0008]	[0.0008]
Municipality FE	Yes	No	Yes	No
Municipality-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)			26.3	29.5
p-value PM 2.5 (weak inst.)			0.000	0.000
Mean DV	32.078	32.078	32.078	32.078
Observations	345,820	345,820	345,820	345,820

Note: This table reports IV estimates of equation (1) at the municipality level. The dependent variable is the logarithm of respiratory ER visits. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include municipality and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. Estimates are weighted by the number of residents in the relevant age group. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by municipality, are reported in brackets. Significance levels are indicated by $* < .1$, ** $< .05$, *** $< .01$.

Table A.3: IV estimates of the effect of PM 2.5 on respiratory ER rates at municipality level.

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5, same day (μg / m^3)	1.855**	1.444**	15.376***	16.222***
	[0.706]	[0.599]	[4.546]	[4.542]
Municipality FE	Yes	No	Yes	No
Municipality-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)			33.8	29.2
p-value PM 2.5 (weak inst.)			0.000	0.000
Mean DV	2,650	2,650	2,650	2,650
Observations	345,820	345,820	345,820	345,820

Note: This table reports IV estimates of equation (1) at the municipality level. The dependent variable is the respiratory ER visit rate per million of residents in the relevant age group. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include municipality and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $*$ $< .1$, ** $< .05$, *** $< .01$.

Table A.4: OLS and IV estimates of the effect of PM 2.5 on (log) respiratory ER visits. Balanced panel of hospitals.

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5 (μg / m^3)	0.0002**	0.0002**	0.0032***	0.0037***
	[0.0001]	[0.0001]	[0.0005]	[0.0004]
Hospital FE	Yes	No	Yes	No
Hospital-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)			197.2	199.1
p-value PM 2.5 (weak inst.)			0.000	0.000
Mean DV	8.391	8.391	8.391	8.391
Observations	2,281,110	2,281,110	2,281,110	2,281,110

Note: This table reports OLS and IV estimates of equation (1) using a balanced panel of hospitals, i.e. hospitals with measures of PM 2.5 in each year of the sample. The dependent variable is the logarithm of respiratory ER visits. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include hospital and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table A.5: OLS and IV estimates of the effect of PM 2.5 on (log) respiratory ER visits. Weighted regression at the hospital level.

	OLS		IV/2SLS	
	(1)	(2)	(3)	(4)
PM 2.5 (μg / m^3)	0.0003***	0.0003***	0.0033***	0.0034***
	[0.0001]	[0.0001]	[0.0004]	[0.0003]
Hospital FE	Yes	No	Yes	No
Hospital-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)			269.6	255.4
p-value PM 2.5 (weak inst.)			0.000	0.000
Mean DV	8.165	8.165	8.165	8.165
Observations	2,618,750	2,618,750	2,618,750	2,618,750

Note: This table reports OLS and IV estimates of equation (1) where estimates are weighted by the average number of annual ER visits in the relevant age group. The dependent variable is the logarithm of respiratory ER visits. The instruments for $PM2.5$ are wind speed at three different pressure levels: 725 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 18). All specifications include hospital and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and ground-level wind speed. The test for weak instruments uses the F statistics and p-values from Sanderson and Windmeijer (2016). Standard errors, clustered by hospital, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.