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

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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 high pollution levels across all age groups. We find that a one 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 and significant for all age groups. Furthermore, the coefficients on government environmental alerts suggest that avoidance behavior becomes increasingly significant across all age groups as restrictions become more severe.

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. Fine particulate matter (PM 2.5) is an important source of air pollution, especially in urban areas. PM 2.5 are tiny particles with diameters smaller than 2.5 micrometers that, when inhaled, get deep into the lungs or the bloodstream, causing various health problems such as decreased lung function, aggravated asthma, irregular heartbeat, etc.[1] In this paper, we study the short-term effect of PM 2.5 exposure on respiratory emergency room (ER) visits across the age distribution, using data from Chile, a middle-income country with high air pollution levels.[2]

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 more infectious respiratory diseases may lead to more ER visits. Third, measuring the true exposure to air pollution is challenging. 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, which can directly affect health.

To overcome the threats to identification described above, we use air pollution data and a rich administrative dataset on ER visits covering Chilean hospitals between 2013 and 2019. We have daily PM 2.5 measures from 80 monitors located across the country and daily information on total ER visits by age group and cause of admission for all hospitals in the 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. Suppose people only travel short distances for an ER visit. In that case, we also have a more accurate measure of pollution exposure for the individual who visits the hospital for an emergency

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

[2] The World Health Organization (WHO) emphasizes the need to carefully examine the health impact of pollution in highly 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)).

episode.

We estimate the effect of PM 2.5 on ER visits using wind speed at different altitudes as instruments, surface 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 surface 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*). In addition to controlling for surface wind speed, we show that the correlation between wind speed at the surface and wind speed at different altitudes is very low. Thus, it is unlikely that wind speed at different altitudes directly affects ER visits, only affecting health through pollution.

Our results 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. Furthermore, we find that this effect is present across all age groups. Our results are robust to controlling for lags in the pollution variables, to using alternative instruments and functional forms, and to perform the analysis at the municipality level.

We further analyze avoidance behavior using the Chilean environmental alert system comprising three categories: *Alert*, *Pre-Emergency*, and *Emergency*. Our results suggest that avoidance behavior tends to intensify as the severity of the restrictions increases. Specifically, we observe that a *Pre-Emergency* declaration decreases ER visits by between 3.5 and 6.8 percent. In comparison, an *Emergency* declaration reduces visits by between 7.9 (for infants) and 19.4 percent (for adults aged 65 and over). Our findings are consistent with those of Mullins and Bharadwaj (2015), who find that environmental alerts in the Metropolitan Region lead to fewer deaths among older adults due to respiratory causes. In the case of ER visits, our results suggest effects across most age groups. Our findings also suggest the potential benefits of reducing the thresholds for pre-emergency and emergency declarations, aligning them to international standards.

We also examine the effect on respiratory ER visits by cause of admission and find that acute respiratory illnesses are the main driver of the results for all age groups. However, chronic respiratory illnesses are also important for older people. Although we do not find significant effects on total circulatory visits, we do find an effect on strokes which is consistent with literature linking PM2.5 exposure with cardiovascular mortality (Gong et al., 2023; Godzinski and Castillo, 2021) and with specific medical literature linking air pollution with strokes, such as Brook et al. (2009), Feigin et al. (2016), Lee et al. (2018), and Xu et al. (2022).

When we divide our sample by geographical region, we find that pollution affects age groups differently depending on the geographic location, which may be related to the different sources of emissions in the different regions. Specifically, we find that PM 2.5 exposure affects all age groups in the Southern regions, where residential wood burning is the primary source of emissions. This highlights the need for policies that promote energy efficiency and cleaner fuels sources.

Finally, to approximate the health cost of the impact of PM 2.5 on ER, we use the daily PM2.5 concentration in 2018 as our baseline and simulate counterfactual scenarios by reducing the average annual PM2.5 from 22.8 µg/m3 (the average PM2.5 in 2018) to 20, 15, 10, and 5 µg/m3 (the recommended air quality level by the WHO). Our calculations suggest a decrease between 1.2 and 7.5 percent in total ER health costs depending on the scenario, representing between 26 and 165 million US dollars.

Our paper relates to the recent literature studying the effects of PM 2.5 on health outcomes.[3] Deryugina et al. (2019) use administrative Medicare data and daily pollution by US counties from 1999 to 2013 to study the impact of PM 2.5 exposure on older adults mortality, health care utilization, and medical costs. They find that an increase in PM 2.5 leads to more ER visits, hospitalizations, mortality, and 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 one 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. Godzinski and Castillo (2021) disentangle the impact of various air pollutants by using multiple instruments and studying 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 has no significant effects on respiratory ER admissions.

Unlike our paper, these studies consider only selected age groups (Deryugina et al., 2019) or find an impact only for some age groups (Godzinski and Castillo, 2021). Our dataset allows us to identify the effect of higher pollution levels which may explain why we find effects for all age groups. This is important because many developing countries' pollution levels are much higher than in developed economies.

[3]Furthermore, this work is related to the broad literature that studies the relationship 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).

Our data come from Chile, a middle-income country with elevated levels of air pollution. According to OECD data, the mean population exposure to PM 2.5 in Chile was 23.7 micrograms per cubic meter (µg/m3) in 2019, while the average in the US was less than 10 µg/m3 and the average in the OECD was 13.9 µg/m3. When we compare our results with Deryugina et al. (2019), who considered ER visits in the US, we find effects that are 2.5 times larger. In that sense, our paper is closer to recent literature identifying the effect of pollution on mortality and life expectancy in China, a highly contaminated country (Gong et al. 2023; Tanaka 2015; Ebenstein et al. 2015, 2017; Chen et al. 2013; Gong et al. 2023; He et al. 2016).

Finally, our work also relates to papers that use Chilean data to identify the effect of pollution on health outcomes, including Bharadwaj et al. (2017); Mullins and Bharadwaj (2015); Rivera et al. (2021); Rivera (2021); Ruiz-Tagle (2019); Ruiz-Tagle and Schueftan (2021). Additionally, our paper is close to Ruiz-Tagle (2019), which investigates the effect of PM2.5 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 PM2.5 increases respiratory ER visits by 8.2 percent. However, our paper relies on a different identification strategy and uses data from all over the country.

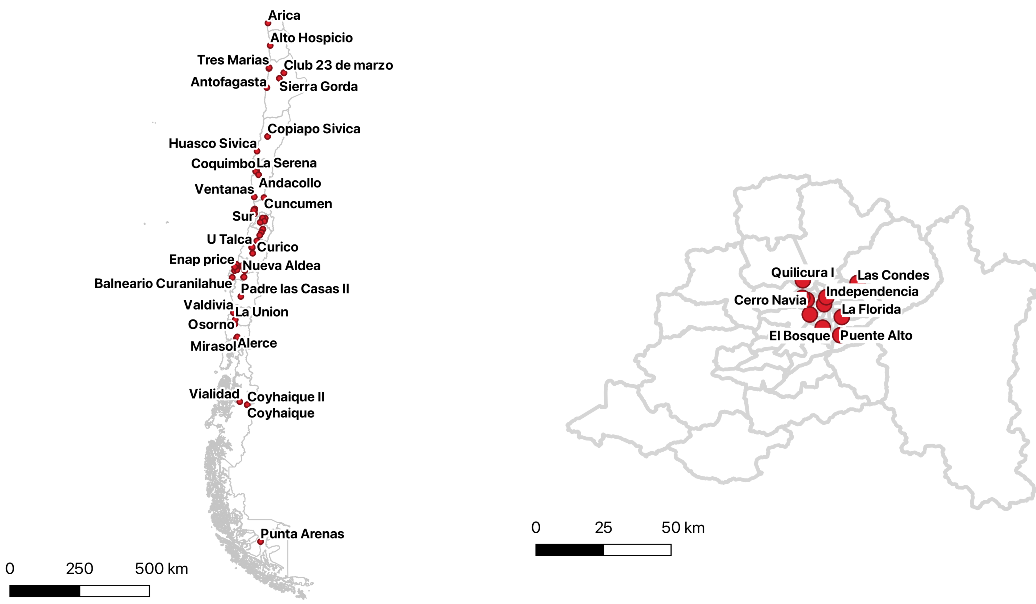
Our paper is organized as follows. Section 2 describes the data. Section 3 presents the empirical model. Section 4 discusses the results. Finally, we run the robustness checks in Section 5 and conclude in Section 6.

2 Data

2.1 Air pollution

We obtain air pollution data from the Air Quality National Information System (SINCA) of the Chilean Ministry of Environmental Affairs.[4] The SINCA collects hourly information on different pollutants, which we use to construct average daily air pollution measures. 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 80 monitors for the period 2013-2019. We use all stations collecting PM 2.5 data in 2013. Between 2013-2019 some monitors stopped reporting, and some new monitors started reporting. Overall,

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

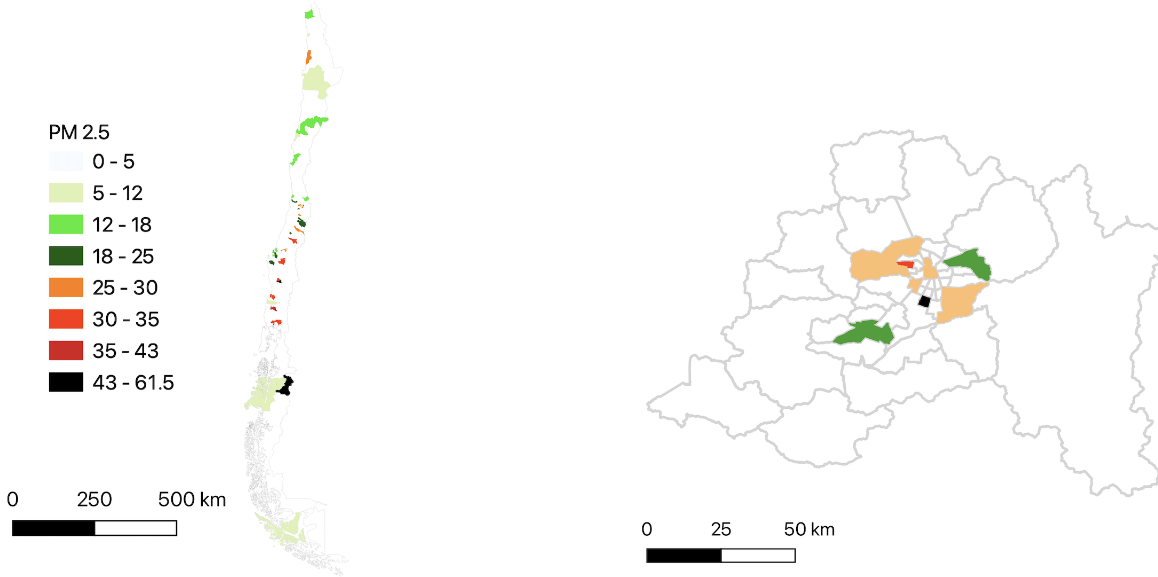


(a) All Monitors

(b) Monitors in Santiago Metropolitan Area

Figure 1: Geographic distribution of Monitors

we have 56 monitors in 2013 and 80 in 2019. The monitors are 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 industrial activity. Chile has 16 regions, with 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). Generally, 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 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.[5] 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.[6] 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.

2.2 Air quality alerts

The *Ministry of Environment* provides data on air quality episodes. This environmental alert system is active during the colder months in thirteen geographical areas in central-south Chile, including the Santiago Metropolitan Area.[7]

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

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

[7] The system is active for a fixed period each 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

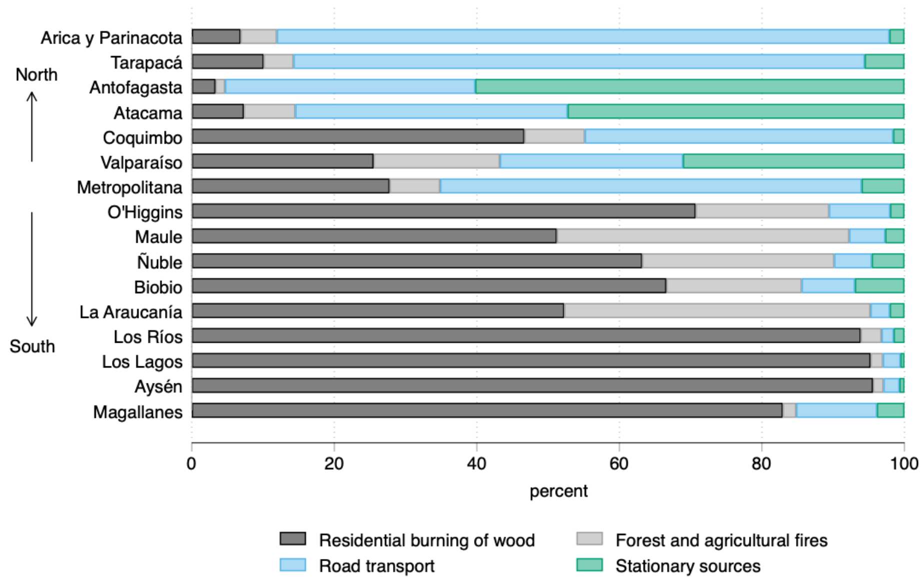


Figure 3: PM 2.5 emission share by source and region, 2018-2019

The issuance of air quality episodes relies 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 that the 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 the PM 2.5 level is expected to be between 80 and 109 $\mu g/m^3$; a *Pre-emergency* episode is issued when the PM 2.5 level is expected to be between 110 and 169 $\mu g/m^3$, and an *Emergency* episode is issued when the PM 2.5 level is expected to be higher than 170 $\mu g/m^3$.

Measures under the *Alert* category include suspension of physical education classes at schools, restricting 40% of vehicles without catalytic converters, and a total ban on the use of wood-burning heaters. The restrictions on vehicles without catalytic converters increase to 60% and 80% during the *Pre-emergency* and *Emergency* episodes, respectively. Furthermore, during *Emergency* days, there is also a restriction of 40% on the rest of the vehicles. On top of that, during *Pre-emergency* and *Emergency* days, the most polluting industries cannot operate, and private cars on congested avenues cannot circulate, allowing only public transportation.

Metropolitan Area and between April 1 and September 30 for Temuco and Padre de las Casas.

2.3 Atmospheric Conditions

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

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 from weather stations owned by the *Dirección Meteorológica de Chile* and the *Dirección General de Aguas*. In total, 295 stations report hourly temperatures, and 816 stations report hourly precipitation. We use the hourly data to compute the daily maximum and minimum temperature and cumulative precipitation.[8] 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 Research and Applications, Version 2 (MERRA-2).[9] 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 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 the 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 locations with SINCA monitors measuring either PM 2.5 or wind speed. Finally, for each layer, we convert the average u- and v-component into wind speed and then average wind speed at the daily level.

[8]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 two 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 precipitation values. 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. We did the same for minimum temperatures.

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

2.4 Emergency department visits

We obtain data on ER visits from Chile's Ministry of Health.[10] The dataset includes all daily ER visits in Chile for 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 fall 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 within a 10 km radius of a monitor as our observation unit. 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 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 those individuals who visit the ER. We select the period 2013–2019 because few monitors measure PM 2.5 before 2013.[11]

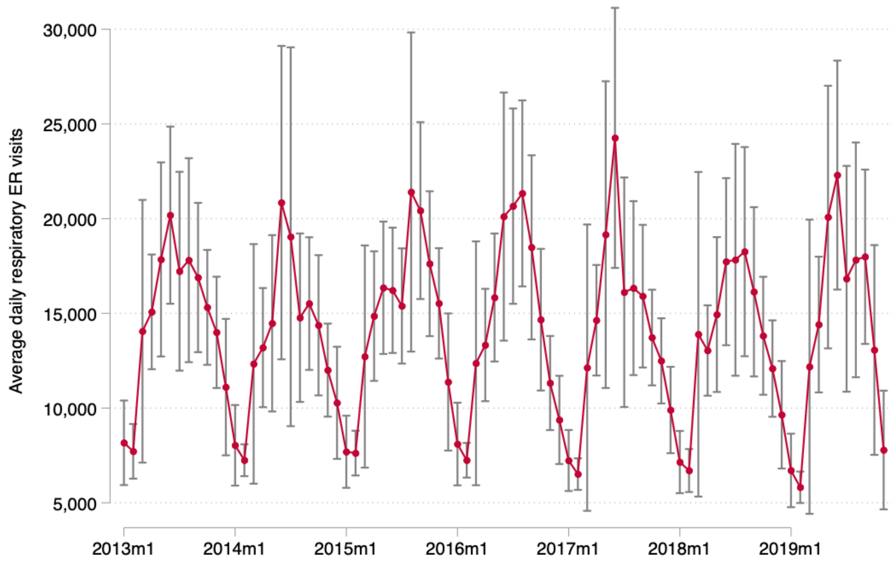
Table 1 shows our sample´s number of hospitals and observations by year. Since the number of monitors increases over time, the number of hospitals we can match also increases.[12]

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. Of 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

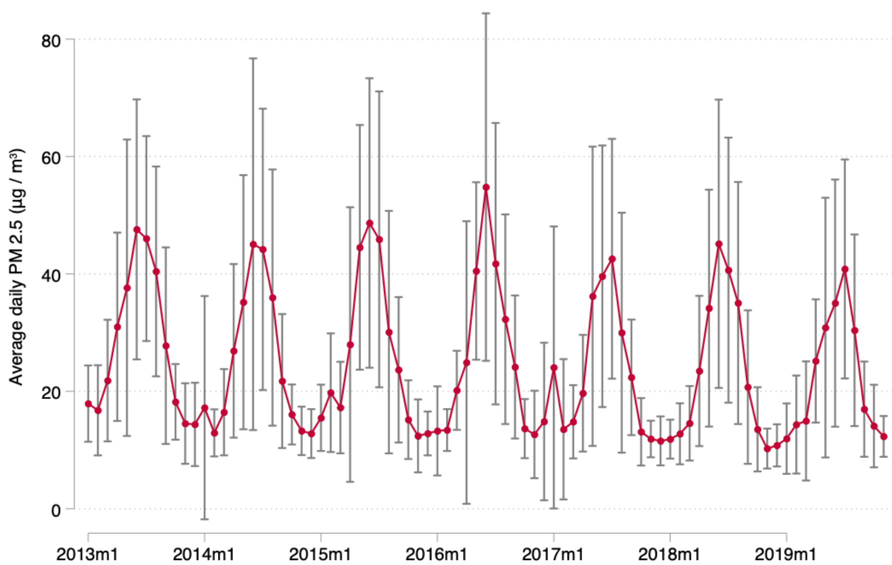
[10] Data are available from the *Departamento de Estadísticas e Información de la Salud* (DEIS) at https://deis.minsal.cl.

[11] Our results are robust to selecting a uniform radius of 10 or 20 km for air pollution monitors and weather stations. See Section 5 for details.

[12] In Section 5, we confirm that the entry/exit of monitors does not drive our results. We estimate our main model with a balanced sample of monitors 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

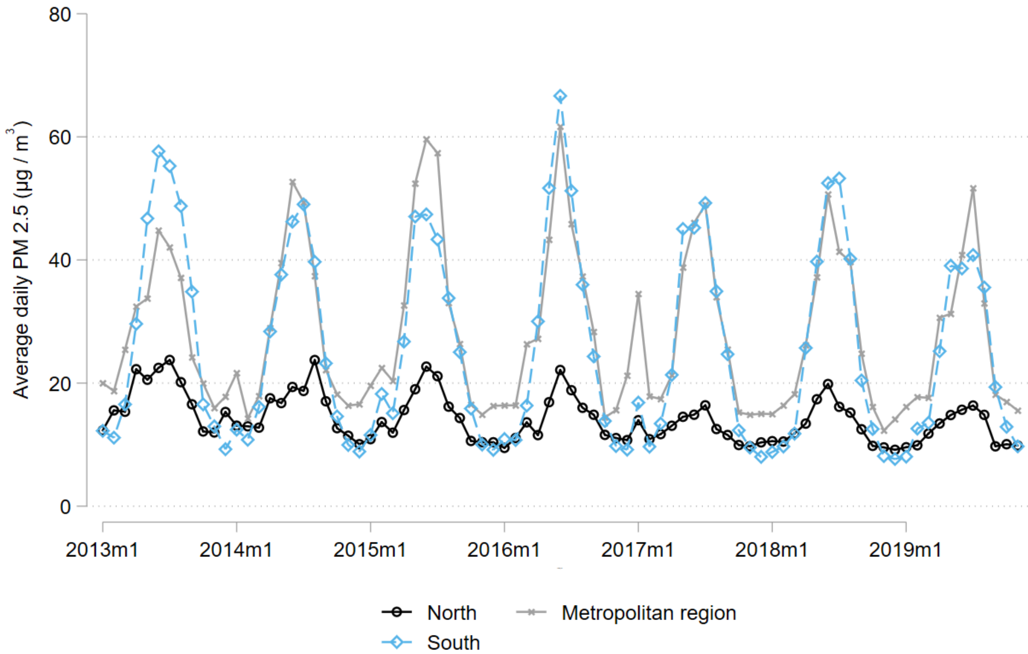


Figure 5: Average daily PM 2.5 concentration by region

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)). Both variables are highly seasonal and highly correlated with each other. Also, 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. 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.

2.5 Average health costs of ER visits

To estimate the average health cost associated with an ER visit, we use claims data (*Prestaciones Bonificadas*) from private insurance for 2018.[13] Claims data provides billing information for each procedure performed by a health provider. To define a health episode, we use the variable *programa medico* that groups various procedures in the same bill.

To calculate the average cost of an ER visit, we identify health episodes that include a procedure code for an ER visit and sum up all the procedures in the episode. We then computed the average episode cost for different age groups. However, we cannot distinguish between respiratory and non-respiratory ER visits, so we approximate respiratory ER visits using claims data only from the second and third quarters when most of respiratory ER visits occur. Additionally, we exclude health episodes with procedure codes related to non-respiratory conditions, such as x-rays of specific body parts, consultations with clinical psychologists, blood lipase tests, certain ultrasounds, and VDRL tests.

Figure 6 shows the average cost of an ER visit for each age group. The average cost of an ER visit is 336,000 Chilean pesos (equivalent to 491 US dollars) for children aged 0-5, 186,000 Chilean pesos (equivalent to 272 US dollars) for children aged 6-10, and then increasing with age from 166,000 Chilean pesos (equivalent to 243 US dollars) for children aged 11-15 to 383,000 Chilean pesos (equivalent to 560 US dollars) for individuals aged 60-65, and 1,000,000 Chilean pesos (equivalent to 1,500 US dollars) for those over 65 years old. Our measure of ER cost is comprehensive, including the ER visit, other procedures, and, if necessary, hospitalization expenses.

[13] These data are publicly available at https://www.supersalud.gob.cl/documentacion/666/w3-propertyvalue-6988.html. Unfortunately, similar data are not available for public insurance.

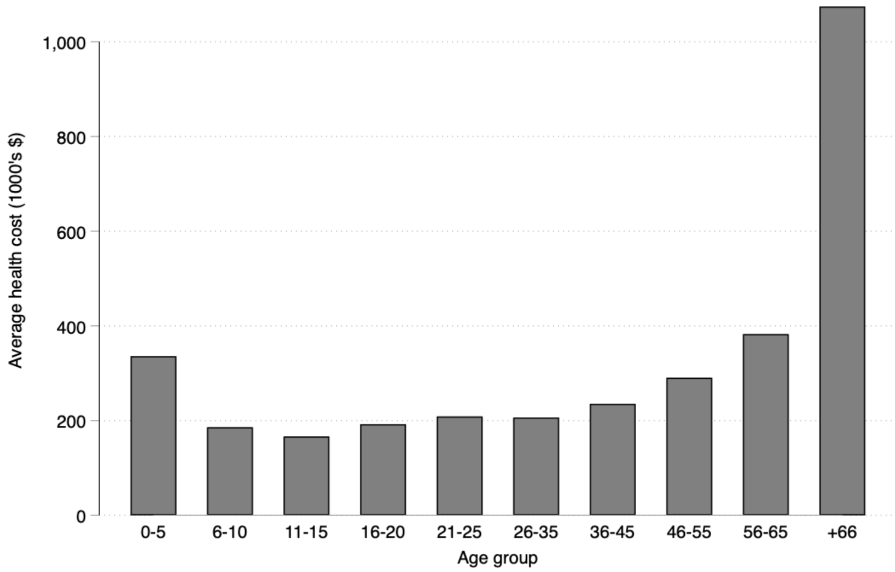


Figure 6: Average health cost for each ER visit by age group, 2018.

3 Empirical Strategy

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

$$Y_{hadmy} = \beta_0 + \beta_1 PM2.5_{hdmy} + \sum_j \delta^j Alert^j_{hdmy} + X'_{hdmy}\gamma + \alpha_a + \alpha_{hy} + \alpha_{dmy} + \epsilon_{hadmy}, \quad (1)$$

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; $Alert^j_{hdmy}$ are dummy variables indicating if the government issues an environmental *Alert*, *Pre-emergency*, or *Emergency* warning for air pollution in the area of 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.

Our main specification 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).

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 surface 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).[14] 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 surface wind speed.[15]

Recent studies show evidence of a correlation between surface PM concentration and altitude wind speed in several regions of different countries. Tong et al. (2018) observed a significant impact of altitude wind speed on PM10 levels in the Pearl River Delta region within the Guangdong-Hong Kong-Macao Greater Bay Area. Additionally, Yim et al. (2019) and Yang et al. (2019) identified correlations between vertical wind profiles and PM2.5 as well as PM10 concentrations in Hong Kong. Furthermore, Yim et al. (2019) reported similar findings for Japan and South Korea.

The literature proposes several mechanisms to explain this evidence. Firstly, wind speed at higher altitudes can transport pollutants from distant regions to the local area (Yim et al. 2019). Secondly, smaller vertical velocity variance indicates atmospheric stability, which

[14] When we estimate the model with all the layers between 12 and 18, we find similar results.

[15] Other papers using similar instruments are, for example, Schwartz et al. (2017) or Godzinski and Castillo (2021).

can lead to the accumulation of air pollutants within the planetary boundary layer (Zhang et al., 2020; Sun et al., 2022; Yang et al., 2019). Note that our instrument also captures vertical velocity variance, as we use wind speed data at different altitudes while controlling for surface wind speed.[16]

In the case of Chile, evidence to determine which of these mechanisms are most prominent is still limited. However, for the Metropolitan Region, Olivares et al. (2023) find that the influence of non-local sources may not be as substantial, suggesting that the second mechanism could be more relevant. This observation aligns with the negative coefficients for altitude wind speed we observed in the first-stage regression, as shown in Table 11 of the paper.

Our instrument satisfies the exclusion restriction because we use surface 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. We expect some correlation between wind speed at the ground and altitude wind, and for this reason, it is crucial to control for surface wind speed in a flexible way. The relevance condition requires that altitude wind speed is correlated with PM 2.5 once we control for surface wind speed.

The specification for the first stage of the IV is

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

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 20).

Although we control for surface wind speed, a high correlation between altitude and surface wind speed may present two problems. Firstly, altitude wind speed could capture some of the surface wind speed that the ground monitor is unable to measure, potentially compromising the exclusion restriction for our instrument. This is more likely if altitude

[16]In addition, meteorological variables at higher altitudes can significantly influence surface pollutant concentrations more than their surface-level counterparts. This is because meteorological variables at higher altitudes typically exhibit less variability due to reduced susceptibility to topographic effects (Tong et al. (2018)).

and surface wind speed are highly correlated. Secondly, if altitude and surface wind speed are highly correlated, the relevance condition may be less likely to be satisfied, as there may not be enough variation in altitude wind speed once we have controlled for surface wind speed.To alleviate these concerns about our instrument, we have analyzed the correlation between surface and altitude wind speed at different levels of altitude. Table 4 presents the correlation matrix between surface wind speed and altitude wind speed at the three levels examined in the paper: 25 hPa (layer 12), 550 hPa (layer 16), and 450 hPa (layer 20). The correlation between surface wind speed and altitude wind speed is low and even becomes negative at high altitudes. Specifically, the correlation between surface wind speed and altitude wind speed at layer 12 is positive (0.08) but shifts to negative at layer 16 (-0.02). In fact, surface wind speed does not exhibit a significant correlation with the various levels of altitude wind speed, which instead appear to be strongly interrelated among themselves. Furthermore, in Section 5, we show that our results are robust to different functional forms for surface wind speed.

To further enhance the credibility of our instruments, we also show in Section 5 that our results are robust to the choice of specific altitude wind speed layers and alternative instruments used in the literature, such as inverse planetary boundary layer height (IPBLH) and thermal inversion.

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

4 Results

Table 5 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) show the estimates without controlling for alerts, and columns (2) and (4) show our preferred specification, which includes dummies for the three alert categories. We estimate that an increase in one $\mu g/m^3$ in PM 2.5 increases respiratory ER visits from 0.36 to 0.38 percentage points. These results are twelve times larger than the OLS estimates.[17] The estimated effect is not negligible: a one standard deviation increase in PM 2.5 (around 24 $\mu g/m^3$) increases respiratory ER visits by 8 percentage points. Moreover, the coefficients of the three categories of environmental alerts suggest a negative impact of avoidance behavior on ER visits which increases with the severity of the restrictions. The test of weak instruments in the first stage has an F-

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

stat of 272.9, showing that the instruments satisfy the relevance condition necessary for identification in the IV estimation.

Using our preferred specification, we explore heterogeneous effects by age group in Figure 7 and Table 6. 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. We find that for the 15-64 age group, a one $\mu g/m^3$ increase in PM 2.5 leads to a 0.34 percent increase in respiratory ER visits. 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 pollution levels, every age group is affected by a higher PM 2.5 concentration.

As observed in the overall population, the results by age suggest that avoidance behavior tends to intensify across all age groups as the severity of the restrictions increases. Specifically, we observe that a *Pre-emergency* declaration decreases ER visits by between 3.5 and 6.8 percent, while an environmental *Emergency* declaration reduces visits by between 7.9 (for infants, although not statistically significant) and 19.4 percent (for adults age 65 and over). Note that the measures have similar effects on all age groups, except for infants under one year old and adults older than 65, who experience slightly larger effects.

The lack of significant results in infants could be due to caregivers not exposing newborns to severe weather conditions, regardless of the pollution. Additionally, the greater flexibility of older adults to stay at home on high-pollution days may explain why they are more susceptible to the alert system. Moreover, *Alert* days have a marginally significant impact on children aged 5-14, possibly due to the suspension of physical education classes at schools. This last result is consistent with the findings of Mullins and Bharadwaj (2015), which indicate that environmental alerts in the Metropolitan Region reduce respiratory-related deaths among older adults.

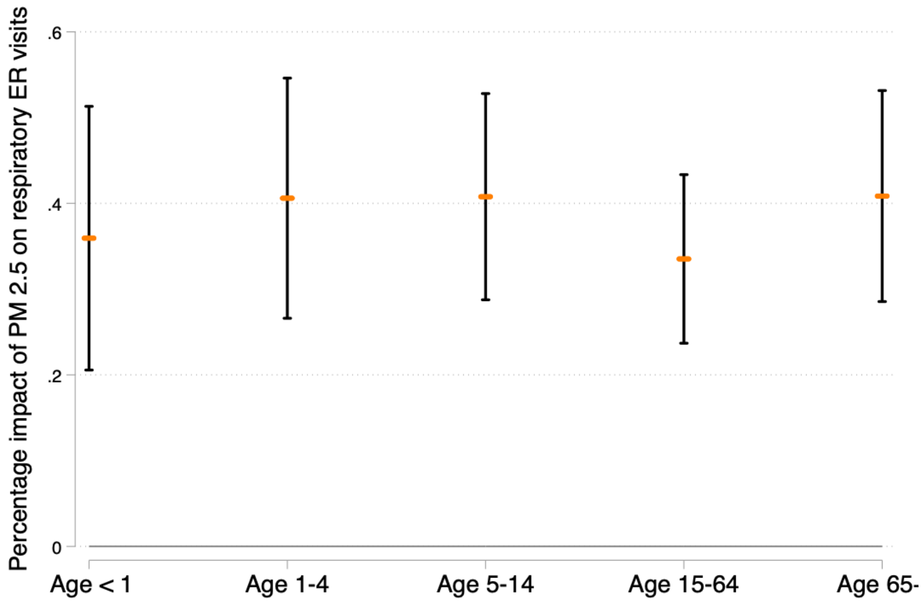


Figure 7: IV estimates of the effect of PM 2.5 on (log) respiratory ER visits, by age group

Table 7 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).

Table 8 reports the results for ER visits due to different types of ER visits: respiratory illnesses (columns (1)), traffic accidents (column (2)), and circulatory causes (column (3)).

Column (2) of Table 8 shows that there is not a significant effect of PM 2.5 on ER visits due to traffic accidents. Our results contrast those of Sager (2019), who finds a positive impact of PM 2.5 on the number of road traffic accidents in the United Kingdom. One possible explanation for the disparate results in our and Sager's paper is that Sager (2019) studies the effect of PM 2.5 concentration on road traffic accidents involving personal injury reported to the police in the United Kingdom, while we consider people who visited the ER after a traffic accident in Chile. If car accidents that require an ER visit are likely to be reported to the police, our sample is more selected than the one in Sager (2019). Thus, one plausible explanation is that pollution does not impact car accidents with more severe consequences. In this sense, our results are similar to Ward (2015), who finds no effect of

PM 2.5 exposure on hospital admissions due to external accidents in Canada. Moreover, as Sager (2019) acknowledges, extrapolating his results to other countries with varying road networks, traffic policies, automotive technologies, and weather conditions is challenging. Therefore, these national differences might account for the divergent results between the UK and Chile.

Column (3) of Table 8 shows that there is not a significant effect of PM 2.5 on ER visits due to circulatory causes. Previous studies, such as Gong et al. (2023) and Godzinski and Castillo (2021) find evidence that PM2.5 exposure increases cardiovascular mortality but its effect on ER visits or admissions is less clear. In particular, using data from France, Godzinski and Castillo (2021) find a significant and positive effect of PM2.5 on cardiovascular mortality, but they do not find any effect on cardiovascular emergency admissions. In their paper, they explain that the impact of PM 2.5 on cardiovascular events could be acute enough to lead directly to death without an ER visit, mainly if it concerns older adults. That could explain why we have not found effects on total circulatory ER admissions.

We also study whether there is an impact on different circulatory ER visits, including myocardial infarction (MI), stroke, hypertensive crisis (HTC), arrhythmia, and other circulatory causes.Table 9 presents these results. Our findings reveal a significant effect of PM2.5 on strokes, which is consistent with the results of Brook et al. (2009). In their randomized controlled trial, treatment groups were exposed to fine particles and particles plus ozone. They find that particles (not ozone) increased the diastolic blood pressure of treated individuals. According to the authors, the increase in blood pressure explains the association between PM2.5 and strokes. Our result is also consistent with other recent papers from the medical literature that also link air pollution with strokes (Feigin et al. (2016), Lee et al. (2018), and Xu et al. (2022)).

Given the difference between pollution levels in different parts of the country, in Table 10 and Figure 8, 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). Notice that, for example, in the North, where mining activities are important, we only observe impact in older children and adults, but not in older adults or young children. However, in the Santiago Metropolitan Area, where road transport is the dominant source, the effect is concentrated in young children (age 0-5). Finally, notice that

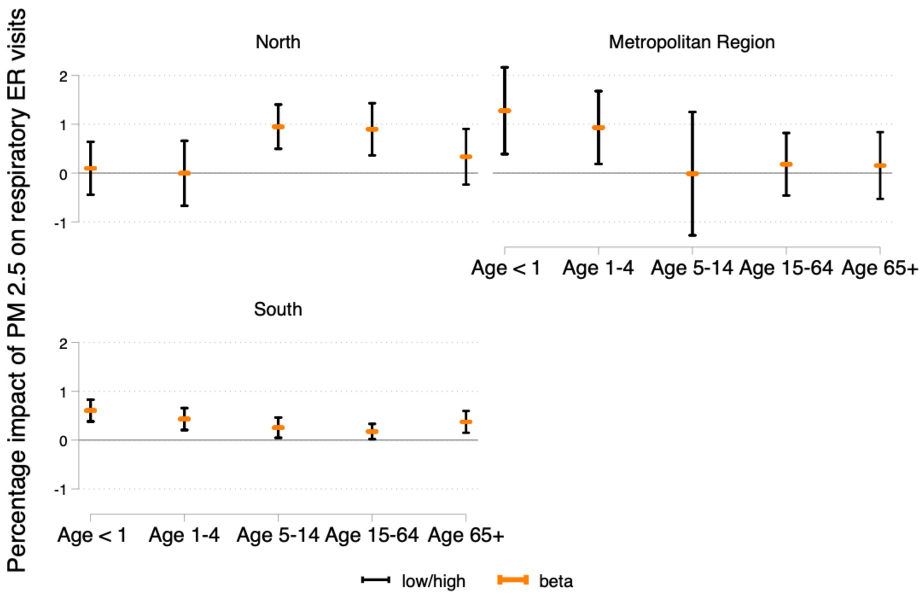


Figure 8: IV estimates of the effect of PM 2.5 on (log) respiratory ER visits by region

in the South, where the primary source of pollution is residential wood 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.

Health costs associated with the impact of PM 2.5 on ER visits

In this section, we approximate the health cost of the impact of PM 2.5 on ER visits. We use the daily PM2.5 concentration in 2018 as our baseline, and we simulate various counterfactual scenarios by reducing the average annual PM2.5 from 22.8 µg/m3 (the average PM2.5 in 2018) to 20, 15, 10, and 5 µg/m3 (the last number is the recommended air quality level by the WHO). Figure 9 shows the daily PM 2.5 concentration for the baseline and counterfactual scenarios. We scale each daily observation in the baseline by the same factor to obtain the average annual PM2.5 in the counterfactual scenario while preserving the seasonal variation in the data.

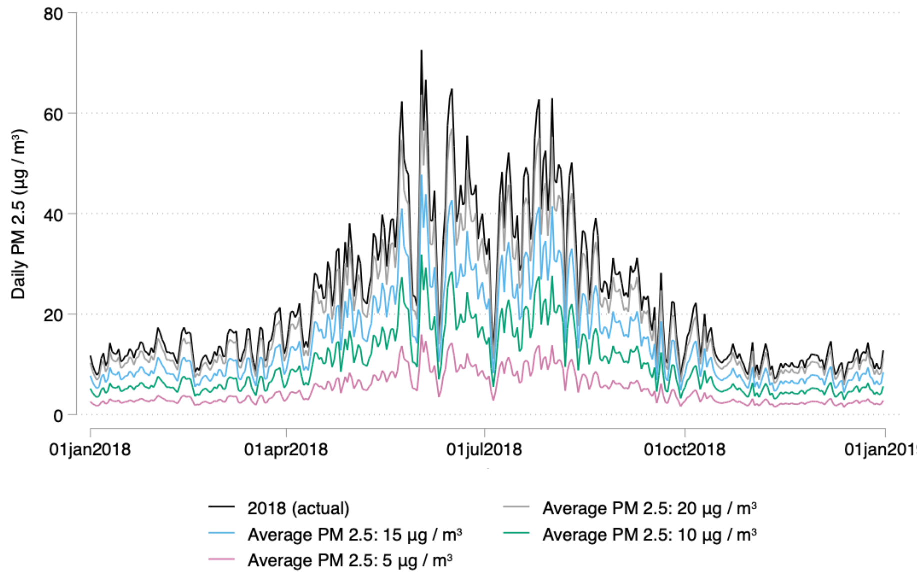


Figure 9: PM 2.5 concentration: 2018 and counterfactual scenarios

To determine the impact of reducing PM 2.5 on ER healthcare costs in the different scenarios, we simulate the effect of PM 2.5 reduction on ER visits for each age group and then aggregate the effects using the average health costs for each group, as follows:

$$\Delta\text{Health costs} = \sum_a Avg\,health\,cost_a\Big[\sum(\widehat{\beta_a} \times ER\,visits_{at}) \times \Delta PM2.5_t\Big],$$

where $\Delta PM2.5_t$ denotes the change in PM 2.5 on date t in a counterfactual scenario, $ER\,visits_{at}$ is the ER visits for age group a on date t in the baseline, $\widehat{\beta_a}$ is the estimated impact for age group a in the main specification, and $Avg\,health\,cost_a$ is the average ER cost for age group a. .

Figures 10 and 11 show each counterfactual scenario's ER visit and total ER health cost changes. In the 20 $\mu g/m^3$ PM 2.5 scenario, ER visits decreased by 57,000, while in the 5 $\mu g/m^3$ PM 2.5 scenario, they decreased by 363,000. ER health costs decreased by 18,000 million Chilean pesos (equivalent to 26 million US dollars) in the 20 $\mu g/m^3$ PM 2.5 scenario and by 113,000 million Chilean pesos (equivalent to 165 million US dollars) in the 5 $\mu g/m^3$ PM 2.5 scenario. These are substantial effects, representing a decrease between 1.2 and 7.5 percent in total ER health costs.

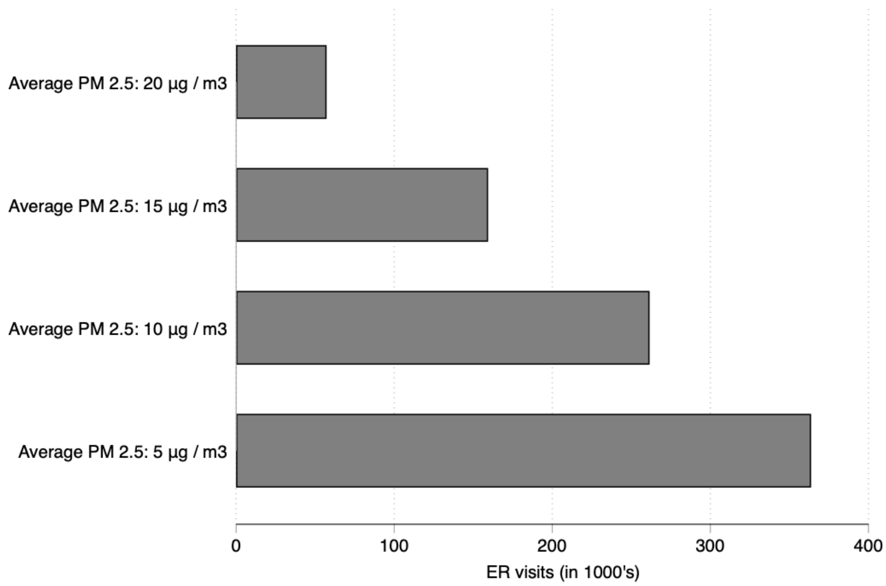


Figure 10: Change in ER visits for the different counterfactual scenarios

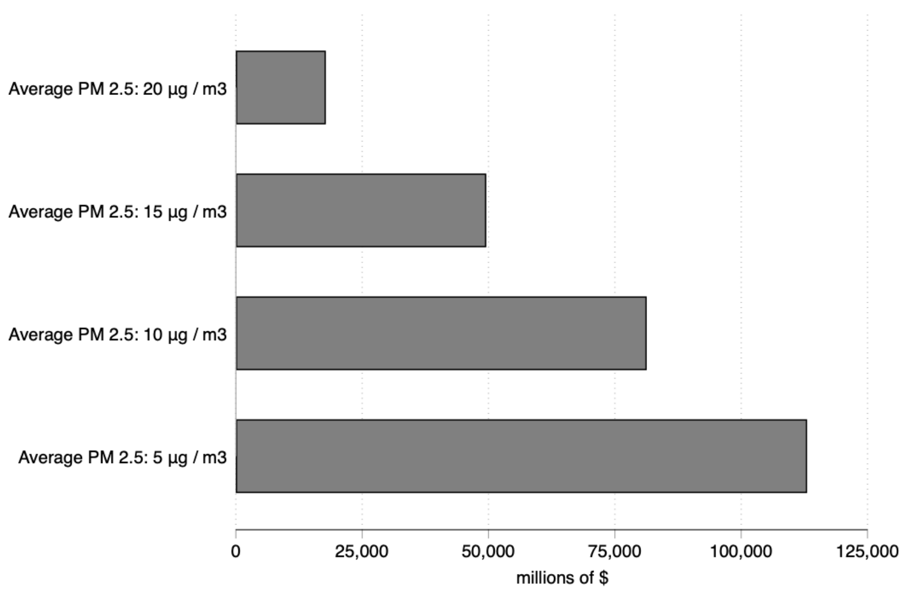


Figure 11: Change in ER health costs for the different counterfactual scenarios

5 Robustness Checks

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

First, to address potential concerns that the validity of our IV specification may depend on the functional form for wind speed or the choice of altitude wind speed layers, we show that our results are robust to these decisions in Table 11. This table shows the IV estimates (Panel A) and first-stage regression results (Panel B) for different specifications using linear and quadratic forms of surface wind speed and different combinations of our three altitude wind speed instruments. Column (1) controls for several indicators for different ranges of surface wind speed (our baseline model), column (2) controls for linear and quadratic forms of surface wind speed, columns (3) to (5) maintain the same functional form for surface wind speed but each column uses only one layer of altitude wind speed as an instrument (layer 12, 16 and 20 respectively). We find that our results are robust to changes in the functional form for surface wind speed (column (1) versus column (2)) or using different layers of altitude wind speed as instruments (column (2) versus columns (3), (4) and (5)). When we use only level 16 wind speed as the instrument, which has a weak negative correlation with surface wind speed (-0.02), the coefficient of PM 2.5 remains practically unchanged. Furthermore, the coefficient of surface wind speed is stable even when level 12 wind speed, which is positively correlated with surface wind speed, is used as the only instrument.

Second, to check whether our results are sensitive to the instruments chosen, we use the inverse PBLH and thermal inversion (an indicator if the temperature difference between the two pressure levels closest to the ground is positive) as alternative instruments. Tables 12 and 13 compare our main results with an alternative specification using thermal inversion and inverse PBLH (at hours 0, 6, and 18) as instruments for PM 2.5. The results are generally similar, although less precise for infants younger than one-year-old and insignificant for adults aged 65 and over. These findings give additional credibility to our instruments. Moreover, we prefer to use altitude wind speed because there is a gain in precision compared to these alternative instruments.

Third, 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 comparing our results, we estimate our preferred specification at this level with the respiratory ER visit rate per million residents as the dependent variable. Tables 14 and 15 show the results of this exercise. In Table 14, we find that an increase in one $\mu g/m^3$ 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 one $\mu g/m^3$ 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 15) 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 pollution in our data, which leads to bigger effects. Table 15 confirms that, with this alternative specification, we find a significant impact for all ages. In Tables A.1, A.2 and A.3 in the Online Appendix, we repeat this analysis with the logarithm of respiratory ER visits as the dependent variable and without weights, with similar results.

Fourth, to provide robustness in our choice of the dependent variable, we compared it to three alternative approaches: the inverse hyperbolic sine transformation, Poisson pseudo maximum likelihood (PPML) regression, and the ratio of emergency room (ER) visits to the hospital-level population. Table 16 presents alternative specifications where we calculated the effect as a percentage of the mean to facilitate comparison between the different options. Our analysis suggests that the choice of the dependent variable has no significant impact on the results.

Fifth, we also study the cumulative effects of pollution. Table 17 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 18 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, we show that our results are robust to using a balanced panel of monitors using data from the 52 monitors that reported PM 2.5 throughout the entire 2013-2019 period. Our results in Tables A.4 and A.5 in the Online Appendix, are consistent with those from our baseline specification. Moreover, in Tables A.6 and A.7 in the Online Appendix, we present a robustness analysis to evaluate the sensitivity, of our results to the 10 km radius between hospitals and pollution monitors we used in the paper. We found that reducing this distance from the benchmark of 10 km to 3 km led to a halving of the observations. However, this change did not significantly alter the results.

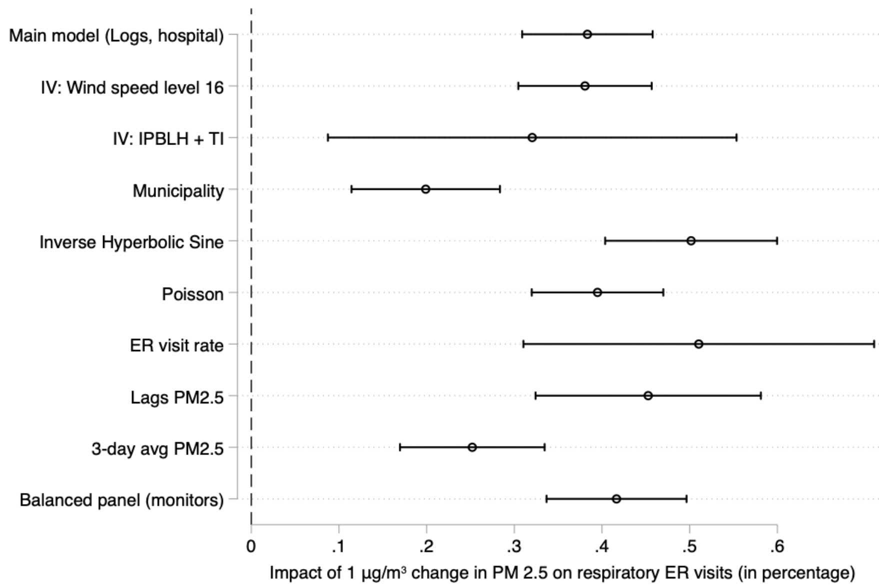


Figure 12: Effect of PM 2.5 on respiratory ER visits. Different specifications.

Figure 12 summarizes the results for the specifications described above and those in the Online Appendix. The effects show that an increase of one $\mu g/m^3$ in PM 2.5 increases respiratory ER visits 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 various 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. When pollution is high, it may affect not only sensitive groups but the whole population.

Our detailed dataset allows us to control for some well-documented problems in this 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 PM 2.5, using surface wind speed as a control variable to instrument air pollution using altitude wind speed. Our instrument satisfies the exclusion restriction because we use surface wind speed as a control variable to capture the direct effect that wind speed may have on health.

We find that an increase of one $\mu g/m^3$ 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. Furthermore, we find similar effects for all age groups. In particular, the impact of PM 2.5 on the 15-64 years old group is similar to the more sensitive groups like children and the older adults (65+).

We also analyze potential avoidance behavior using the Chilean environmental alert system, comprising three categories: *Alert*, *Pre-Emergency*, and *Emergency*. Our results suggest that avoidance behavior tends to intensify across all age groups as the severity of the restrictions increases. Specifically, we find that a *Pre-Emergency* declaration decreases ER visits by between 3.5 and 6.8 percentage points. An *Emergency* declaration has an even greater effect, reducing visits by between 7.9 (although not statistically significant for infants) and 19.4 percentage points for adults aged 65 and over.

We quantified the positive effects of reducing PM 2.5 concentration on ER visits and healthcare costs, showing that achieving the WHO-recommended PM 2.5 annual mean of 5 $\mu g/m^3$ would lead to an annual reduction of 363,000 ER visits and a 7.5 percent decrease in ER healthcare costs. With these substantial health and cost benefits, the next crucial consideration is designing effective environmental policies to achieve these reductions in PM 2.5. We believe that our research offers some insights on this issue.

First, we find that PM 2.5 exposure affects all age groups in regions where residential wood burning is the primary source of emissions. This highlights the need for policies that promote energy efficiency and cleaner fuels sources. In a broader context, it is critical to consider emission sources when designing policies to cut PM 2.5 emissions.

Second, we find that air quality alerts effectively reduce PM 2.5 exposure for all age groups except infants under one year old. However, as shown in Table 5, we only find significant results when authorities declare a pre-emergency or emergency episode (PM 2.5 is expected to be higher than 110 $\mu g/m^3$) but not an alert episode (PM 2.5 is expected to be between 80 and 109 $\mu g/m^3$). These findings suggest the potential benefits of adjusting alert thresholds or the criteria for pre-emergency and emergency declarations. On one hand, the more stringent policies implemented during pre-emergency or emergency episodes (such as increased restrictions on vehicles without catalytic converters or limited circulation in congested avenues) could also be extended to alert episodes. On the other hand, it is worth noting that the initial threshold level to declare an environmental episode is set at a forecasted PM 2.5 level of 80 $\mu g/m^3$ which significantly exceeds the WHO's recommended daily concentration of 15 $\mu g/m^3$. Aligning these thresholds more closely with international practices, such as California's regulations, where wood burning is prohibited at levels exceeding 50 µg/m3 and advisory alerts are issued at levels greater than 12 µg/m3, could yield positive results.[18]

Finally, Chile's alert system is currently limited to areas with high pollution levels (urban areas in the Metropolitan Region and Southern Regions). Extending this policy to cities with lower pollution levels could improve health outcomes, as recent research suggests that health impacts depend on a variety of health and socioeconomic factors related to pollution, not solely pollution levels. (Deryugina et al. (2021)).

[18]For more information, see https://www.sparetheair.org/about/alerts-and-advisories, or http://www.aqmd.gov/home/programs/community/community-detail?title=check-before-you-burn.

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.

Bosilovich, M. G., R. Lucchesi, and M. Suarez (2016). Merra-2: File specification. Technical report, GMAO Office.

Brook, R. D., B. Urch, J. T. Dvonch, R. L. Bard, M. Speck, G. Keeler, M. Morishita, F. J. Marsik, A. S. Kamal, N. Kaciroti, et al. (2009). Insights into the mechanisms and mediators of the effects of air pollution exposure on blood pressure and vascular function in healthy humans. Technical Report 3.

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.

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.

Deryugina, T., N. Miller, D. Molitor, and J. Reif (2021). Geographic and Socioeconomic Heterogeneity in the Benefits of Reducing Air Pollution in the United States. *Environmental and Energy Policy and the Economy 2*, 157 – 189.

Ebenstein, A., M. Fan, M. Greenstone, G. He, P. Yin, and M. Zhou (2015, May). Growth, pollution, and life expectancy: China from 1991-2012. *American Economic Review 105*(5), 226–31.

Ebenstein, A. E., M. Fan, M. Greenstone, G. He, and M. Zhou (2017). New 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 114*(39), 10384–10389.

Feigin, V. L., G. A. Roth, M. Naghavi, P. Parmar, R. Krishnamurthi, S. Chugh, G. A. Mensah, B. Norrving, I. Shiue, M. Ng, K. Estep, K. Cercy, C. J. L. Murray, and M. H. Forouzanfar (2016). Global burden of stroke and risk factors in 188 countries, during 1990-2013: a systematic analysis for the global burden of disease study 2013. *The Lancet Neurology 15*(9), 913–924.

Gelaro, R., W. McCarty, M. J. Suárez, R. Todling, A. Molod, L. Takacs, C. A. Randles, A. Darmenov, M. G. Bosilovich, R. Reichle, K. Wargan, L. Coy, R. Cullather, C. Draper, S. Akella, V. Buchard, A. Conaty, A. M. da Silva, W. Gu, G.-K. Kim, R. Koster, R. Lucchesi, D. Merkova, J. E. Nielsen, G. Partyka, S. Pawson, W. Putman, M. Rienecker, S. D. Schubert, M. Sienkiewicz, and B. Zhao (2017). The Modern-Era Retrospective Analysis for Research and Applications, version 2 (merra-2). *Journal of Climate 30*(14), 5419 – 5454.

Godzinski, A. and M. S. Castillo (2021). Disentangling the effects of air pollutants with many instruments. *Journal of Environmental Economics and Management 109*, 102489.

Gong, Y., S. Li, N. J. Sanders, and G. Shi (2023). The mortality impact of fine particulate matter in China: Evidence from trade shocks. *Journal of Environmental Economics and Management 117*, 102759.

He, G., M. Fan, and M. Zhou (2016). The effect of air pollution on mortality in China: Evidence from the 2008 Beijing Olympic Games. *Journal of Environmental Economics and Management 79*, 18–39.

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

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.

Lee, K. K., M. R. Miller, and A. S. V. Shah (2018, Jan). Air pollution and stroke. *J Stroke 20*(1), 2–11.

Moretti, E. and M. Neidell (2011). Pollution, health, and avoidance behavior: Evidence from the ports of los angeles. *The Journal of Human Resources 46*(1), 154–175.

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. (2009). Information, avoidance behavior, and health: The effect of ozone on asthma hospitalizations. *The Journal of Human Resources 44*(2), 450–478.

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.

Olivares, I., J. Langner, C. Soto, E. A. Monroy-Sahade, A. Espinosa-Calderón, P. Pérez, M. A. Rubio, A. Arellano, and E. Gramsch (2023, October). Vertical distribution of PM2.5 in Santiago de Chile studied with an unmanned aerial vehicle and dispersion modelling. *Atmospheric Environment 310*, 119947.

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. (2021). Air quality warnings and temporary driving bans: Evidence from air pollution, car trips, and mass-transit ridership in santiago. *Journal of Environmental Economics and Management 108*, 102454.

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 (2021). Nudging for cleaner air: Experimental evidence from an rct on wood stove usage. *Environment and Resource Economics* (79), 712–743.

Sager, L. (2019). Estimating the effect of air pollution on road safety using atmospheric temperature inversions. *Journal of Environmental Economics and Management 98*, 102250.

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.

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

Schwartz, J., M.-A. Bind, and P. Koutrakis (2017, 2022/05/11). Estimating causal effects of local air pollution on daily deaths: Effect of low levels. *Environmental Health Perspectives 125*(1), 23–29.

Sun, X., Y. Zhou, T. Zhao, Y. Bai, T. Huo, L. Leng, H. He, and J. Sun (2022, January). Effect of Vertical Wind Shear on PM2.5 Changes over a Receptor Region in Central China. *Remote Sensing 14*(14), 3333.

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.

Tanaka, S. (2015). Environmental regulations on air pollution in china and their impact on infant mortality. *Journal of Health Economics 42*, 90–103.

Tong, C. H. M., S. H. L. Yim, D. Rothenberg, C. Wang, C.-Y. Lin, Y. D. Chen, and N. C. Lau (2018, May). Assessing the impacts of seasonal and vertical atmospheric conditions on air quality over the Pearl River Delta region. *Atmospheric Environment 180*, 69–78.

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.

WHO (2016). Expert consultation: Available evidence for the future update of the who global air quality guidelines (aqgs). Technical report.

Xu, R., Q. Wang, J. Wei, W. Lu, R. Wang, T. Liu, Y. Wang, Z. Fan, Y. Li, L. Xu, C. Shi, G. Li, G. Chen, L. Zhang, Y. Zhou, Y. Liu, and H. Sun (2022, Jul). Association of short-term exposure to ambient air pollution with mortality from ischemic and hemorrhagic stroke. *Eur J Neurol 29*(7), 1994–2005.

Yang, Y., S. H. Yim, J. Haywood, M. Osborne, J. C. Chan, Z. Zeng, and J. C. Cheng (2019). Characteristics of Heavy Particulate Matter Pollution Events Over Hong Kong and Their Relationships With Vertical Wind Profiles Using High-Time-Resolution Doppler Lidar Measurements. *Journal of Geophysical Research: Atmospheres 124*(16), 9609–9623.

Yim, S., X. Hou, J. Guo, and Y. Yang (2019, April). Contribution of local emissions and transboundary air pollution to air quality in Hong Kong during El Niño-Southern Oscillation and heatwaves. *Atmospheric Research 218*, 50–58.

Yim, S. H. L., Y. Gu, M. A. Shapiro, and B. Stephens (2019, October). Air quality and acid deposition impacts of local emissions and transboundary air pollution in Japan and South Korea. *Atmospheric Chemistry and Physics 19*(20), 13309–13323.

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

Zhang, Y., J. Guo, Y. Yang, Y. Wang, and S. H. L. Yim (2020, January). Vertical Wind Shear Modulates Particulate Matter Pollutions: A Perspective from Radar Wind Profiler Observations in Beijing, China. *Remote Sensing 12*(3), 546. Number: 3 Publisher: Multidisciplinary Digital Publishing Institute.

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 estimating sample.

Table 2: Summary statistics, 2013–2019

Variables	Mean	s.d.	Min	Max
Pollution				
PM 2.5 (μg / m^3)	26.32	22.77	0.00	739.35
ER visits				
Respiratory	8.16	9.85	0.00	1103.00
Acute respiratory (J00-J21)	6.81	8.64	0.00	1103.00
Chronic respiratory (J40-J46)	0.44	1.22	0.00	67.00
Other respiratory	0.91	3.05	0.00	280.00
Circulatory	0.55	1.69	0.00	220.00
Traffic accidents	0.14	1.15	0.00	105.00
Weather				
Max. Daily Temp. (Celsius)	20.92	6.36	-2.92	41.19
Min. Daily Temp. (Celsius)	8.96	4.07	-11.20	23.73
Daily precipitation (mm)	1.22	4.96	0.00	108.40
Wind Speed (km/hour)	1.63	0.90	0.00	13.52
Wind Speed (layer 12) (km/hour)	7.97	4.96	0.75	38.65
Wind Speed (layer 16) (km/hour)	14.60	7.00	0.51	48.52
Wind Speed (layer 20) (km/hour)	26.46	11.67	0.77	75.66
Air quality alerts				
Alert	0.053	0.225	0.000	1.000
Preemergency	0.017	0.127	0.000	1.000
Emergency	0.002	0.046	0.000	1.000
Observations	2,618,765			

Note: This table reports descriptive statistics for the estimating 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 20).

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 estimating 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 T-bar is the average number of observations by a hospital in a month (within variation).

Table 4: Correlation matrix for surface and altitude wind

	Surface wind speed	Level 12	Level 16	Level 20
Surface wind speed	1.00			
Level 12	0.08^{***}	1.00		
Level 16	-0.02^{***}	0.82^{***}	1.00	
Level 20	-0.08^{***}	0.63^{***}	0.86^{***}	1.00

Table 5: 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**	0.0036***	0.0038***
	[0.0001]	[0.0001]	[0.0003]	[0.0004]
Alert		0.0243***		-0.0120
		[0.0053]		[0.0084]
Pre-emergency		0.0197**		-0.0545***
		[0.0077]		[0.0136]
Emergency		0.0368**		-0.1440***
		[0.0152]		[0.0295]
F stat PM 2.5 (weak inst.)			272.9	207.3
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. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include hospital-year, day-month-year and age group fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 (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)	0.0036***	0.0041***	0.0041***	0.0034***	0.0041***
	[0.0008]	[0.0007]	[0.0006]	[0.0005]	[0.0006]
Alert	-0.0195	-0.0181	-0.0179*	-0.0040	-0.0007
	[0.0124]	[0.0115]	[0.0105]	[0.0099]	[0.0107]
Pre-emergency	-0.0345*	-0.0509***	-0.0642***	-0.0552***	-0.0679***
	[0.0205]	[0.0195]	[0.0187]	[0.0154]	[0.0187]
Emergency	-0.0793	-0.1495***	-0.1290***	-0.1684***	-0.1939***
	[0.0538]	[0.0438]	[0.0396]	[0.0358]	[0.0379]
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. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include hospital-month and day-month-year fixed effects, controls fpr environmental alerts, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 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)	0.0036***	0.0041***	0.0041***	0.0034***	0.0041***
	[0.0008]	[0.0007]	[0.0006]	[0.0005]	[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)	0.0034***	0.0040***	0.0040***	0.0033***	0.0040***
	[0.0007]	[0.0007]	[0.0007]	[0.0006]	[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	-0.0004	0.0005	0.0007	0.0010**
	[0.0005]	[0.0006]	[0.0004]	[0.0006]	[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	0.0004	0.0005	0.0002	0.0005
	[0.0003]	[0.0005]	[0.0006]	[0.0007]	[0.0004]
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 20). All specifications include hospital and day-month-year fixed effects, controls for environmental alerts, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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: IV estimates of the effect of PM 2.5 on (log) ER visits by ER type

	(1) Respiratory	(2) Traffic accidents	(3) Circulatory
PM 2.5 (μg / m^3)	0.0038***	0.0001	-0.0000
	[0.0004]	[0.0001]	[0.0001]
Alert	-0.0120	-0.0037**	-0.0014
	[0.0084]	[0.0016]	[0.0022]
Pre-emergency	-0.0545***	-0.0036	0.0002
	[0.0136]	[0.0031]	[0.0039]
Emergency	-0.1440***	-0.0206	-0.0058
	[0.0295]	[0.0144]	[0.0094]
F stat PM 2.5 (weak inst.)	207.3	207.3	207.3
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000
Mean DV	8.165	0.144	0.551
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. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include hospital-month and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 different types of circulatory ER visits

	(1) MI	(2) Stroke	(3) HTC	(4) Arrh.	(5) Other
PM 2.5 (μg / m^3)	0.0001	0.0001**	-0.0001	0.0000	-0.0000
	[0.0001]	[0.0001]	[0.0001]	[0.0001]	[0.0001]
Alert	-0.0009	-0.0022**	0.0017	-0.0003	-0.0007
	[0.0007]	[0.0010]	[0.0018]	[0.0008]	[0.0018]
Pre-emergency	-0.0028**	-0.0018	0.0026	-0.0009	0.0019
	[0.0012]	[0.0015]	[0.0031]	[0.0016]	[0.0031]
Emergency	-0.0033	-0.0092**	0.0059	-0.0022	-0.0033
	[0.0035]	[0.0047]	[0.0072]	[0.0038]	[0.0077]
F stat PM 2.5 (weak inst.)	207.3	207.3	207.3	207.3	207.3
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	0.022	0.061	0.216	0.036	0.216
Observations	2,618,765	2,618,765	2,618,765	2,618,765	2,618,765

Note: This table reports IV estimates of equation (1) for different types of circulatory ER visits. The dependent variable is the logarithm of ER visits for the corresponding circulatory ER type: myocardial infarction (MI), stroke, hypertensive crisis (HTC), arrhythmia, or other circulatory causes. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include hospital-month and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 10: 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	3.309	8.958	8.611	14.769	2.398
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	3.296	9.134	8.098	18.158	2.983
Observations	284,163	284,163	284,163	284,163	284,163
Panel C: South					
PM 2.5 (μg / m^3)	0.0060***	0.0043***	0.0026**	0.0018**	0.0037***
	[0.0011]	[0.0011]	[0.0011]	[0.0008]	[0.0011]
F stat PM 2.5 (weak inst.)	47.0	47.0	47.0	47.0	47.0
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	3.127	8.929	8.378	16.770	3.077
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 20). All specifications include hospital-year, day-month-year and age group fixed effects, controls for environmental alerts, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 11: Effect of PM 2.5 on (log) respiratory ER visits. Robustness to different functional forms for surface wind speed and different instruments

	(1)	(2)	(3)	(4)	(5)
Panel A: IV regression					
PM 2.5 (μg / m^3)	0.0038***	0.0038***	0.0034***	0.0037***	0.0041***
	[0.0004]	[0.0004]	[0.0006]	[0.0004]	[0.0005]
Surface wind speed		0.0112***	0.0089**	0.0104***	0.0125***
		[0.0034]	[0.0037]	[0.0033]	[0.0039]
Wind-Precip.-Temp. Interact.	Yes	No	No	No	No
Precip -Temp. Interactions	No	Yes	Yes	Yes	Yes
F stat PM 2.5 (weak inst.)	207.3	239.1	169.9	697.2	731.6
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	8.165	8.165	8.165	8.165	8.165
Panel B: First Stage					
Wind speed level 12	-0.1314***	-0.0167	-0.4184***		
	[0.0488]	[0.0540]	[0.0321]		
Wind speed level 16	-0.2020***	-0.2587***		-0.4045***	
	[0.0184]	[0.0204]		[0.0153]	
Wind speed level 20	-0.0984***	-0.1066***			-0.2274***
	[0.0097]	[0.0106]			[0.0084]
Surface wind speed		-5.5363***	-5.4970***	-5.5275***	-5.6200***
		[0.4379]	[0.4335]	[0.4419]	[0.4492]
Wind-Precip.-Temp. Interact.	Yes	No	No	No	No
Precip. - Temp. Interactions	No	Yes	Yes	Yes	Yes
Mean DV	26.316	26.316	26.316	26.316	26.316
Observations	2,618,765	2,618,765	2,618,765	2,618,765	2,618,765

Note: This table reports IV and first-stage estimates of equation (1). The dependent variable is the log of respiratory ER visits. All specifications include hospital-year, day-month-year and age group fixed effects, controls for enviromental alerts, and flexible controls for temperatures (maximum and minimum), precipitation, and surface wind speed. Alert is a dummy variable indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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: Effect of PM 2.5 on (log) respiratory ER visits. Different instruments

	(1) Wind	(2) IPBLH+TI
PM 2.5 (μg / m^3)	0.0038***	0.0032***
	[0.0004]	[0.0012]
Alert	-0.0120	-0.0058
	[0.0084]	[0.0126]
Pre-emergency	-0.0545***	-0.0418*
	[0.0136]	[0.0253]
Emergency	-0.1440***	-0.1131*
	[0.0295]	[0.0615]
F stat PM 2.5 (weak inst.)	207.3	45.1
p-value PM 2.5 (weak inst.)	0.000	0.000
Mean DV	8.165	8.165
Observations	2,618,765	2,618,765

Note: This table reports IV estimates of equation (1). Column (1) uses altitude wind speed (layers 12, 16, and 20) as instruments, while column (2) uses inverse planetary boundary layer height (IPBLH) and thermal inversion (TI). The dependent variable is the log of respiratory ER visits. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. All specifications include hospital-year, day-month-year and age group fixed effects, controls for enviromental alerts, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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: Effect of PM 2.5 on (log) ER visits by age. Different instruments

	< 1	1-4	5-14	15-64	65 +
Panel A: Wind					
PM 2.5 (μg / m^3)	0.0036***	0.0041***	0.0041***	0.0034***	0.0041***
	[0.0008]	[0.0007]	[0.0006]	[0.0005]	[0.0006]
F stat PM 2.5 (weak inst.)	206.2	206.2	206.2	206.2	206.2
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	3.2	9.0	8.2	17.3	3.0
Observations	523,637	523,637	523,637	523,637	523,637
Panel B: IPBLH + TI					
PM 2.5 (μg / m^3)	0.0025	0.0051***	0.0040**	0.0037**	0.0008
	[0.0022]	[0.0018]	[0.0018]	[0.0017]	[0.0017]
F stat PM 2.5 (weak inst.)	44.9	44.9	44.9	44.9	44.9
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	3.2	9.0	8.2	17.3	3.0
Observations	523,637	523,637	523,637	523,637	523,637

Note: This table reports IV estimates of equation (1) by age group. Panel (A) uses altitude wind speed (layers 12, 16, and 20) as instruments, while panel (B) uses inverse planetary boundary layer height (IPBLH) and thermal inversion (TI). The dependent variable is the log of respiratory ER visits. All specifications include hospital-year, day-month-year and age group fixed effects, controls for environmental alerts, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 14: 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)	0.488*	0.544**	4.485***	5.272***
	[0.277]	[0.245]	[1.084]	[1.144]
Alert		-7.982		-48.178**
		[18.633]		[23.810]
Pre-emergency		-28.774		-115.899***
		[28.894]		[40.819]
Emergency		-67.142		-265.304***
		[66.312]		[72.967]
F stat PM 2.5 (weak inst.)			29.5	24.1
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 100,000 residents in the relevant age group. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include municipality, day-month-year and age group fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 county, are reported in brackets. Significance levels are indicated by $* < .1$, $** < .05$, $*** < .01$.

Table 15: 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)	35.1**	26.1***	10.0***	2.4***	5.6***
	[14.6]	[7.1]	[3.2]	[0.7]	[1.2]
Alert	-367.1*	-250.1***	-112.5**	-20.0	-28.0
	[188.0]	[90.4]	[55.3]	[16.7]	[23.5]
Pre-emergency	-576.2	-512.0***	-234.4**	-58.0**	-108.0**
	[346.3]	[168.8]	[99.5]	[24.3]	[40.9]
Emergency	-454.7	-1275.7***	-516.7***	-147.0***	-256.9***
	[693.8]	[350.6]	[171.6]	[46.3]	[75.5]
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. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include municipality-year and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 16: IV estimates of the effect of PM 2.5 on rate of respiratory ER visits, by age group. Robustness using different transformations of the dependent variable.

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
Dependent variable: Logarithmic transformation					
PM 2.5 (μg / m^3)	0.004***	0.004***	0.004***	0.003***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
F stat PM 2.5 (weak inst.)	206.2	206.2	206.2	206.2	206.2
Effect relative to mean, percent	0.36	0.41	0.41	0.34	0.41
Observations	523,637	523,637	523,637	523,637	523,637
Dependent variable: Inverse hyperbolic sine transformation					
PM 2.5 (μg / m^3)	0.005***	0.005***	0.005***	0.004***	0.005***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
F stat PM 2.5 (weak inst.)	206.2	206.2	206.2	206.2	206.2
Effect relative to mean, percent	0.56	0.51	0.51	0.39	0.62
Observations	523,637	523,637	523,637	523,637	523,637
Dependent variable: Poisson pseudo maximum likelihood regression					
PM 2.5 (μg / m^3)	0.004***	0.004***	0.004***	0.004***	0.006***
	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]
F stat PM 2.5 (weak inst.)	206.2	206.2	206.2	206.2	206.2
Effect relative to mean, percent	0.41	0.39	0.42	0.36	0.63
Observations	507,918	507,922	507,922	511,086	510,768
Dependent variable: Ratio ER visits to population					
PM 2.5 (μg / m^3)	27.056*	29.612***	10.086***	3.083***	7.369***
	[14.706]	[5.831]	[3.200]	[0.804]	[1.052]
F stat PM 2.5 (weak inst.)	165.1	169.9	153.4	157.8	162.6
Effect relative to mean, percent	0.40	0.59	0.53	0.46	0.96
Observations	523,637	523,637	523,637	523,637	523,637

Note: This table reports IV estimates of equation (1) by age group. The first panel (baseline model) shows the results for a logarithm transformation ($log(1+ER\,visits)$), the second panel for a inverse hyperbolic sine transformation ($arcsinh(ER\,visits)$), the third panel for a Poisson pseudo maximum likelihood regression, and the fourth panel for a ratio of ER visits to population where population is computed using the population living in census blocks within 5 km of the hospital.
All specifications include hospital-month and day-month-year fixed effects, control for environmental alerts, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 17: 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	0.0045***	0.0045***
	[0.0001]	[0.0001]	[0.0007]	[0.0007]
PM 2.5, 1-day lag (μg / m^3)	0.0001	0.0001	-0.0014	-0.0013
	[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]
Alert		0.0132**		-0.0102
		[0.0056]		[0.0086]
Pre-emergency		0.0113		-0.0352**
		[0.0084]		[0.0159]
Emergency		0.0218		-0.0942***
		[0.0180]		[0.0335]
F stat PM 2.5 (weak inst.)			114.3	111.8
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. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). 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 surface 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 18: 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***	0.0002**	0.0024***	0.0025***
	[0.0001]	[0.0001]	[0.0004]	[0.0004]
Alert		0.0187***		-0.0028
		[0.0050]		[0.0072]
Pre-emergency		0.0133*		-0.0338***
		[0.0076]		[0.0125]
Emergency		0.0319**		-0.0735***
		[0.0142]		[0.0249]
F stat PM 2.5 (weak inst.)			183.8	164.6
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. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include hospital, day-month-year and age group fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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: 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)	0.000	0.000	0.004***	0.004***
	[0.000]	[0.000]	[0.001]	[0.001]
Alert		0.022*		-0.023
		[0.013]		[0.020]
Pre-emergency		0.004		-0.092***
		[0.014]		[0.033]
Emergency		0.006		-0.208***
		[0.020]		[0.068]
F stat PM 2.5 (weak inst.)			29.2	23.8
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. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include municipality and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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: 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)	-0.000	-0.000	0.002***	0.003***
	[0.000]	[0.000]	[0.001]	[0.001]
Alert		0.013		-0.013
		[0.014]		[0.017]
Pre-emergency		-0.009		-0.064***
		[0.014]		[0.021]
Emergency		-0.046		-0.171***
		[0.029]		[0.034]
F stat PM 2.5 (weak inst.)			29.5	24.1
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. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include municipality and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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: 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)	1.444**	1.365**	16.222***	18.455***
	[0.599]	[0.568]	[4.542]	[5.112]
Alert		30.949		-144.946**
		[62.529]		[65.160]
Pre-emergency		6.780		-367.850***
		[77.575]		[126.346]
Emergency		105.056		-730.464**
		[107.107]		[279.533]
F stat PM 2.5 (weak inst.)			29.2	23.8
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. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include municipality and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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: Effect of PM 2.5 on (log) respiratory ER visits. Robustness using a balanced sample of monitors.

	Full sample		Balanced sample	
	(1)	(2)	(3)	(4)
PM 2.5 (μg / m^3)	0.0035***	0.0038***	0.0038***	0.0042***
	[0.0005]	[0.0004]	[0.0005]	[0.0004]
Alert	-0.0129	-0.0120	-0.0261**	-0.0236**
	[0.0099]	[0.0084]	[0.0108]	[0.0092]
Pre-emergency	-0.0470***	-0.0545***	-0.0704***	-0.0761***
	[0.0161]	[0.0136]	[0.0186]	[0.0160]
Emergency	-0.1252***	-0.1440***	-0.1695***	-0.1883***
	[0.0343]	[0.0295]	[0.0384]	[0.0331]
Hospital FE	Yes	No	Yes	No
Hospital-Year FE	No	Yes	No	Yes
F stat PM 2.5 (weak inst.)	226.0	207.3	165.4	162.5
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000
Mean DV	8.165	8.165	8.245	8.245
Observations	2,618,765	2,618,765	2,477,515	2,477,515

Note: This table reports IV estimates of equation (1) for the full sample and a balanced sample of monitors, i.e. monitors that reported PM 2.5 during the entire 2013-2019 period.
The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution.
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 20). All specifications include hospital-month and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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: Effect of PM 2.5 on (log) respiratory ER visits, by age group. Robustness using a balanced sample of monitors.

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
Full sample					
PM 2.5 (μg / m^3)	0.0036***	0.0041***	0.0041***	0.0034***	0.0041***
	[0.0008]	[0.0007]	[0.0006]	[0.0005]	[0.0006]
F stat PM 2.5 (weak inst.)	206.2	206.2	206.2	206.2	206.2
Mean DV	3.236	9.043	8.248	17.335	2.962
Observations	523,637	523,637	523,637	523,637	523,637
Balanced sample of monitors					
PM 2.5 (μg / m^3)	0.0045***	0.0049***	0.0037***	0.0033***	0.0045***
	[0.0008]	[0.0007]	[0.0006]	[0.0005]	[0.0007]
F stat PM 2.5 (weak inst.)	161.6	161.6	161.6	161.6	161.6
Mean DV	3.266	9.119	8.318	17.516	3.007
Observations	495,391	495,391	495,391	495,391	495,391

Note: This table reports IV estimates of equation (1) by age group using a balanced sample of monitors, i.e. monitors that reported PM 2.5 during the entire 2013-2019 period.
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 20). All specifications include hospital-month and day-month-year fixed effects, controls for enviromental alerts, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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.6: Effect of PM 2.5 on log of respiratory ER visits. Robustness using different distances from pollution monitors to hospitals

	(1) 3 km	(2) 5 km	(3) 10 km	(4) 20 km
PM 2.5 (μg / m^3)	0.0036***	0.0037***	0.0038***	0.0035***
	[0.0005]	[0.0004]	[0.0004]	[0.0003]
Alert	-0.0143	-0.0128	-0.0120	-0.0070
	[0.0118]	[0.0093]	[0.0084]	[0.0074]
Pre-emergency	-0.0546***	-0.0507***	-0.0545***	-0.0425***
	[0.0184]	[0.0148]	[0.0136]	[0.0128]
Emergency	-0.1334***	-0.1365***	-0.1440***	-0.1205***
	[0.0366]	[0.0319]	[0.0295]	[0.0272]
Hospital-Year FE	Yes	Yes	Yes	Yes
F stat PM 2.5 (weak inst.)	93.2	155.8	207.3	246.1
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000
Mean DV	7.937	8.122	8.165	7.985
Observations	1,323,045	2,117,125	2,618,765	2,888,895

Note: This table reports IV estimates of equation (1) for different samples. Each column reports a sample using a hospitals within some distance to a pollution monitor (3, 5, 10,, or 20 km). The dependent variable is the logarithm of respiratory ER visits in the corresponding age group. Alert, Pre-emergency and Emergency are dummy variables indicating if the government issues an alert, pre-emergency, or emergency warning for air pollution. 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 20). All specifications include hospital-month and day-month-year fixed effects, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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.7: Effect of PM 2.5 on log of respiratory ER visits, by age group. Robustness using different distances from pollution monitors to hospitals

	(1) < 1	(2) 1-4	(3) 5-14	(4) 15-64	(5) 65 +
Distance pollution monitor to hospital: 3 km					
PM 2.5 (μg / m^3)	0.004***	0.004***	0.003***	0.003***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
F stat PM 2.5 (weak inst.)	92.2	92.2	92.2	92.2	92.2
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	3.4	9.2	8.0	16.0	3.0
Observations	264,502	264,502	264,502	264,502	264,502
Distance pollution monitor to hospital: 5 km					
PM 2.5 (μg / m^3)	0.004***	0.004***	0.004***	0.003***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
F stat PM 2.5 (weak inst.)	154.8	154.8	154.8	154.8	154.8
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	3.4	9.1	8.2	16.9	3.0
Observations	423,310	423,310	423,310	423,310	423,310
Distance pollution monitor to hospital: 10 km (main model)					
PM 2.5 (μg / m^3)	0.004***	0.004***	0.004***	0.003***	0.004***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
F stat PM 2.5 (weak inst.)	206.2	206.2	206.2	206.2	206.2
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	3.2	9.0	8.2	17.3	3.0
Observations	523,637	523,637	523,637	523,637	523,637
Distance pollution monitor to hospital: 20 km					
PM 2.5 (μg / m^3)	0.003***	0.004***	0.004***	0.003***	0.004***
	[0.001]	[0.001]	[0.001]	[0.000]	[0.001]
F stat PM 2.5 (weak inst.)	244.9	244.9	244.9	244.9	244.9
p-value PM 2.5 (weak inst.)	0.000	0.000	0.000	0.000	0.000
Mean DV	3.1	8.8	8.1	17.0	2.9
Observations	577,649	577,649	577,649	577,649	577,649

Note: This table reports IV estimates of equation (1) by age group for different samples. Each column reports a sample using a hospitals within some distance to a pollution momitor (5, 10, 15, or 20 km). 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 20). All specifications include hospital-month and day-month-year fixed effects, controls for enviromental alerts, and flexible controls for temperatures (maximum and minimum), precipitation, and surface 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 $*<.1$, $**<.05$, $***<.01$.