Putting a price tag on air pollution: the social healthcare costs of air pollution in France

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Abstract

I estimate the causal effects of air pollution on healthcare costs in France by combining administrative data on healthcare reimbursements with reanalysis data on air pollution concentrations and weather conditions. I adopt an instrumental variable approach where I exploit daily postcode-level variation in nitrogen dioxide, ground-level ozone and particulate matter concentrations induced by variation in wind speed. I explore effect heterogeneity by patient and location characteristics and by medical speciality. This study presents evidence for substantial healthcare costs caused by exposure to pollution levels that are predominantly situated below current European limit values. The effects are several orders of magnitude larger than those estimated in previous studies, suggesting that the healthcare costs of air pollution have been severely underestimated. I find significant heterogeneity of effects by location and patient characteristics, indicating that air pollution reduction policies have the potential to reduce health inequalities.

Key words: Air pollution, health care cost, wind speed.
JEL codes: I12, J14, Q51, Q53

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1 Introduction

Exposure to air pollution has well-documented adverse effects on human health, such as the increased risk of cardiovascular and respiratory disease and cancer. In 2016, air pollution was estimated to contribute to 7.6% of worldwide deaths (WHO, 2017). In response, many countries have put in place air quality standards and objectives for a number of pollutants present in the air. However, it is often argued that these standards are set arbitrarily, without conclusive evidence of health benefits to be weighed against the costs of pollution reduction to producers and consumers. Accurate information on the benefits of reducing air pollution is essential to determine the optimal level of environmental policy, particularly in cases where pollution levels are already relatively low and further pollution reductions are likely to be costly. In this study, I comprehensively quantify the healthcare costs caused by acute exposure to air pollution in France where pollution levels are on average below the current European limit values.

Estimating the causal effects of air pollution on healthcare use and costs is difficult due to endogeneity problems and a general lack of adequate data. People sort spatially according to preferences and characteristics that may correlate with their health status and pollution exposure. Families with higher incomes or preferences for cleaner air are likely to sort in locations with lower air pollution (Chay and Greenstone, 2003; Chen et al., 2018). Alternatively, individuals with a high level of education and income may choose to live in urban areas where pollution levels are on average higher. Failure to consider such non-random exposure to air pollution results in biased estimates. Without information on incomes or preferences, many researchers have relied on quasi-experimental designs that use a plausibly exogenous source of pollution variation to estimate the causal effects of air pollution on health. However, these studies are usually limited to relatively narrow geographical areas and periods, consider only a specific part of the population or study the effects of pollution on a limited selection of health conditions. Much of this work considers avoided mortality costs. Mortality is a rather extreme event that is less likely to occur following exposure to moderate pollution levels. The cost of moderate health effects that are likely caused by exposure to moderate levels of air pollution are often not considered.

In this study, I investigate the causal effects of acute exposure to nitrogen dioxide (NO2), ground-level ozone (O3) and fine particles pollution (PM 10) on healthcare use and costs in a representative sample of the French population. I combine unique administrative data on daily healthcare costs with reanalysis data on daily pollution levels and weather conditions at postcode area level. The data range from 2015 to 2018 and includes information on the nature of medical acts and associated costs of treatment for all types of healthcare, including physician visits, drug purchases, and hospital care. I adopt an instrumental variable (IV) approach where I instrument for air pollution using changes in wind speed. It is generally well established that wind speed strongly affects pollution concentrations by carrying certain pollutants away from their source of origin, causing them to disperse. The identifying assumption is that variation in pollution due to changes in wind speed is unrelated to changes in healthcare use or costs except through the influence on air pollution. After flexibly controlling for various time and location fixed effects and meteorological conditions, this assumption should hold. Outside of extreme events, wind speed is unlikely to affect health directly (other than through its effect on air pollution). For 99% of the observations in my data, the wind speed is lower than a level 4 on the Beaufort scale, which is described as a moderate breeze that lifts dust and paper and moves small branches (Royal Meteorological Society).

To the best of my knowledge, this is the first quasi-experimental study to comprehensively quantify the healthcare costs caused by exposure to moderate levels of air pollution in a nationwide representative sample. I also explore effect heterogeneity in greater depth than most previous studies. Using variation in pollution levels across a broad geographic scale enables me to rigorously explore treatment effect heterogeneity by location characteristics such as average income and unemployment rates. I investigate whether the effects vary by patient characteristics, including age, chronic disease status and socioeconomic status, assuming that being covered by a publicly funded supplementary health insurance scheme available to low-income households indicates low socioeconomic status. Finally, I examine what types of health conditions are affected by exposure to air pollution by running separate regressions for a selection of 15 different medical specialities. While interesting in its own right, this exercise also serves as a sanity check. I consider both medical specialities that should be affected by air pollution (such as cardiology and vascular medicine or pulmonology) and medical specialities that should not be affected (such as plastic surgery or trauma surgery), which serve as placebo.

In further extensions of this work, I study the effects of air pollution on sick leave and mortality and consider wind direction and thermal inversions as alternative instrumental variables. For the analyses by medical specialities, I also consider strike periods in the public transport sector as an instrument for air pollution. It has been shown that air pollution levels are influenced by episodes of public transport strikes as people switch from public transport to cars which increases pollution from road traffic (van Exel and Rietveld, 2001; Bauernschuster et al., 2017; Basagaña et al., 2018; Godzinski and Suarez Castillo, 2019). The exclusion restriction for this instrument should hold for some selected medical specialities, such as cardiovascular and respiratory care, which I analyse separately from other medical specialities that could be affected by the occurrence of strikes, such as, for example, trauma surgery due to changes in road traffic accidents.

I find that each 1 $\mu g/m^3$ increase in daily NO2 (7.2% of the mean) causes an increase of €7.57 in postcode area healthcare spending area whereas each 1 $\mu g/m^3$ increase in daily O3 (1.8% of the mean) causes €3.94 higher spending. This corresponds to an increase of 1.5% and 0.8% relative to the average daily postcode area healthcare spending. The results for particulate matter pollution are generally less significant and less robust across different model specifications. The estimates in this study reflect the costs of acute (short-term) exposure to air pollution without considering the potentially more significant effects of long-term exposure. Yet, the costs of short-term exposure alone suggest that there are considerable benefits to reducing air pollution. Summing across postcode areas and scaling the effect to the size of the entire French population, the estimated effects translate to an increase in additional healthcare spending of €6.8 million per day or €2.5 billion per year. To put this into perspective, the cost of complying with the National Emission Commitment (NEC) Directive (2016/2284/EU)[1] for France has been estimated to be €9.9 billion per year (Amann et al., 2017). Using my estimates, I calculate that the further reduction in NO2 pollution levels required to meet the NEC goal results in an annual saving of €5.2 billion in healthcare costs per year. This means that the benefits from a reduction in healthcare costs due to the decreased NO2 pollution alone (disregarding the changes in other pollutant levels and effects on mortality or productivity, natural systems, etc.) set off over 50% of the total costs of compliance with the NEC directive.

I find considerable effect heterogeneity by patient characteristics and postcode areas. The effects are 2.5 to 6.5 times larger in big cities. I also find 1.2 to 4.8 times stronger effects in the population that suffers from a chronic disease. While most studies find adverse health effects among the youngest and elderly population, I find evidence of effects across all age categories. The estimated level effect is higher for individuals 40 years and older, while the effect relative to average age group spending is more similar across age groups. This is likely due to the fact that most studies find stronger effects in the young and the elderly in terms of mortality, which is a rather extreme event likely to affect only the most vulnerable. In contrast, I am interested in healthcare costs that include the costs of treating milder health effects that seem to occur in all age groups. The analyses of heterogeneity by medical specialty encouragingly show that there are no effects of pollution for the placebo medical specialties. The categories affected are mainly expenditure on primary care or family physicians and ambulance services. In the French context, this makes sense as patients have to go through their primary physician who then refers them to specialists in order to be reimbursed, while the increased use of ambulance services suggests an increase in emergency hospital admissions.

This study contributes to the recent quasi-experimental literature on the health effects of air pollution. The idea of exploiting short-run exogenous shocks such as air pollution alerts, public transport strikes, changes in wind direction, thermal inversions to estimate the causal effects of air pollution on health is not new. An example of a recent paper using meteorological conditions is Deryugina et al. (2019), which

[1]Directive (EU) 2016/2284 of the European Parliament and of the Council of 14 December 2016 on the reduction of national emissions of certain atmospheric pollutants, amending Directive 2003/35/EC and repealing Directive 2001/81, `https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016L2284&from=EN`

estimates the causal effects of acute fine particulate matter exposure on mortality, healthcare use, and medical costs by instrumenting for air pollution using changes in local wind direction. However, Deryugina et al. (2019) is limited to studying the population of the US elderly as they employ Medicare data. In fact, most of the existing quasi-experimental studies focus on a relatively narrow geographic area or on events that are limited in time, often consider only a specific part of the population and/or investigate the effects of pollution on a limited selection of health conditions (Ransom and Iii, 1995; Pope III and Dockery, 1999; Friedman et al., 2001; Chay and Greenstone, 2003; Neidell, 2004; Currie and Neidell, 2005; Jayachandran, 2009; Neidell, 2009; Moretti and Neidell, 2011; Currie and Walker, 2011; Chen et al., 2013; Anderson, 2015; Schlenker and Walker, 2015; Knittel et al., 2016; Schwartz et al., 2016; Deschênes et al., 2017; Deryugina et al., 2019; Simeonova et al., 2019; Halliday et al., 2019). Much of this work considers avoided mortality costs. This is a rather extreme event that is less likely to occur following exposure to moderate pollution levels. Overall healthcare costs related to the treatment of conditions caused or aggravated by air pollution are generally not quantified as detailed information on healthcare spending is rarely available. My study goes beyond this literature by comprehensively quantifying the healthcare caused by exposure to moderate levels of air pollution in a nationwide representative sample, exploiting data on all types of healthcare and health conditions and the exact costs of treatment. Having data on a representative population sample, notably all age groups, and observations across a broad geographic scale enables me to rigorously explore treatment effect heterogeneity by patient and location characteristics.

This study also contributes to the literature on measuring the health costs of air pollution for cost-benefit analysis to inform policy making. Most studies that seek to evaluate the health costs of air pollution for cost-benefit analysis estimate the costs indirectly through simulations based on air quality and population data, baseline rates of mortality and morbidity, concentration-response parameters from the epidemiological literature, and unit economic values. Often, only a selection of health effects for which epidemiological evidence is most robust is included in these models. I am not aware of any study that comprehensively quantifies healthcare costs of air pollution in France. For example, a 2015 Senate Committee of Inquiry into the economic and financial cost of air pollution[2] searched for estimates of the total costs of air pollution to the French healthcare system to inform policy decisions. The result was a report on two studies that considered only asthma and cancer (Fontaine et al., 2007) or respiratory diseases and cancers, and hospitalisations for respiratory and cardiovascular causes in Rafenberg (2015). Probably the most comparable study in its ambition to comprehensively quantify the healthcare costs of air pollution and the pollutants considered is the study by Pimpin et al. (2018) using UK data. Yet even this study only considered a limited number

[2]In French the "Commission d'enqute sur le cot conomique et financier de la pollution de l'air". http://www.senat.fr/rap/r14-610-1/r14-610-11.pdf

of health problems (asthma, COPD, coronary heart disease, stroke, type 2 diabetes, dementia and lung cancer). The authors estimate that a 1 $\mu g/m^3$ reduction in population exposure to PM2.5 and NO2 would result in savings of 98.5 million per year in NHS and social care costs in a population of comparable size to that of France [3]. This is orders of magnitude lower than the costs I estimate. While the existing studies clearly state that the healthcare cost estimates are conservative, the extent to which total effects have been underestimated has been unknown. My estimates put into perspective the extent to which total health care costs have been underestimated.

This study presents evidence of sizeable healthcare costs caused by acute exposure to air pollution at levels that are mostly below current European legal limits. The estimates presented here do not take into account the potentially large health effects of long-term exposure, but the estimated costs of short-term exposure alone suggest that there are considerable benefits to further reducing air pollution below current levels. EU air quality rules are presently being revised. One of the policy changes being discussed is a closer alignment of EU air quality standards with scientific knowledge, including the latest recommendations of the World Health Organization (WHO).[4] This planned revision is a step in the good direction. While the WHO limit values are not more stringent than the current EU framework for NO2 and O3, the revision would result in a reduction of the limit values for PM10 from an annual average of 40 $\mu g/m^3$ to 20 $\mu g/m^3$ and for PM2.5 from 25 $\mu g/m^3$ to 10 $\mu g/m^3$. However, this study estimates sizeable healthcare costs caused by levels of air pollution that are on average below or close to the limit values proposed by the WHO. This suggests that even stricter regulation than that of the WHO could still result in significant savings for healthcare systems. Another argument for a further reduction in air pollution is a concern for equity. The study provides evidence for significant heterogeneity of effects across patient characteristics and postcode areas, indicating that air pollution reduction policies have the potential to reduce health inequalities.

The rest of the paper is organised as follows. Section 2 provides a brief background on the health impacts of air pollution, air quality in France and the relation between wind speed and air pollution levels. Section 3 describes the data, Section 4 describes the empirical strategy, Section 5 presents results, Section 6 shows sensitivity analyses and presents some extensions highlighting possibilities for future research. Section 7 discusses the findings and concludes.

[3]The UK population is 66.65 million compared to 67.06 million in France in 2019

[4]https://ec.europa.eu/environment/air/quality/revision_of_the_aaq_directives.htm

2 Background

2.1 Health effects of air pollution and air quality in France

Air pollution is the single largest environmental risk to the health of Europeans, with particulate matter (PM), nitrogen dioxide (NO2) and ground-level ozone (O3) being the pollutants of greatest concern (EEA, 2020). Exposure to PM2.5 has been estimated to be responsible for around 400,000 premature deaths in Europe every year whereas exposure to NO2 and O3 were responsible for around 70,000 and 15,000 premature deaths in 2017, respectively (Maguire et al., 2020). Air pollution has various health effects. Short-term exposure to air pollution is closely related to Chronic Obstructive Pulmonary Disease (COPD), cough, shortness of breath, wheezing, asthma, respiratory disease, and high rates of hospitalisation. NO2 is an irritant of the respiratory system as it penetrates deep in the lung, inducing respiratory diseases, coughing, wheezing, and even pulmonary edema when inhaled at high levels. Systems other than respiratory ones can be involved, as symptoms such as eye, throat, and nose irritation have been registered. Small particulate matter of less than 10 or 2.5 microns in diameter (PM10 and PM2.5) bypass the bodys defences against dust, penetrating deep into the respiratory system. They also comprise a mixture of health-harming substances, such as heavy metals, sulphurs, carbon compounds, and carcinogens including benzene derivatives. Ground-level ozone (O3) is key factor in chronic respiratory diseases such as asthma. Young children, the elderly, and people with lung disease are especially vulnerable to air pollution. The health of susceptible and sensitive individuals can be impacted even on low air pollution days (for a review, see for example Manisalidis et al. (2020)).

Legal air quality standards in France concern levels of nitrogen dioxide (NO2), oxides of nitrogen (NOx), sulphur dioxide (SO2), lead (Pb), particulate matter 10 micrometers or less in diameter (PM10) and 2.5 micrometers or less in diameter (PM2.5), carbon monoxide (CO), benzene (C6H6), ozone (O3), as well as concentrations of arsenic, cadmium, nickel, and benzo[a]pyrene. See Table A1 for a summary of current French air quality standards for the pollutants considered in this study. Air quality in France improved globally over the period 2000-2018 following the implementation for several years of strategies and action plans in various sectors of activity (Farret et al., 2019). Exceedances of regulatory air quality standards still persist, but they are fewer than in the past and affect fewer areas (mainly near road traffic). Figure 2 shows daily mean and daily maximum hourly pollution levels for the pooled postcode day observations relative to the French limit values. Pollution levels are mostly well below the limit value, which means that this study focuses on the impact of pollution levels that are generally considered safe.

2.2 Wind speed and air pollution levels

It is generally well established that wind speed strongly affects the degree of accumulation of NO2 (or more generally NOx) and particulate matter near emission sources such as traffic in urban environments. Wind carries these air contaminants away from their source, causing them to disperse. In general, the higher the wind speed, the more contaminants are dispersed and the lower their concentration (Jones et al., 2010; Cichowicz et al., 2020). For ground-level ozone, in contrast, it has been shown that concentrations are positively correlated with wind speed (Afonso and Pires, 2017; Ordónez et al., 2005). This stems from the general inverse relationship between ground-level ozone and NO2. Ground-level ozone is a secondary pollutant which is formed by the influence of solar radiation from the precursors NOx and volatile organic compounds (VOC). The processes of ozone formation and accumulation are complex. Nitrogen dioxide and oxygen react, which results in nitrogen monoxide and ozone.[5] Being an equilibrium reaction, the reaction also works in the other direction whereby ozone gets degraded again (EPA; Clapp and Jenkin, 2001). Less ozone destruction and thus higher ozone concentrations are expected for high wind speed (as NOx concentrations are lower). High wind speed is also expected to favour vertical mixing which lead to higher ground-level ozone concentrations through increased supply of ozone from the elevated reservoir layer of the atmosphere (Ordónez et al., 2005).

In my data, NO2 and O3 are generally inversely related which is consistent with the pollution dynamics described above. NO2 and particulate matter are positively correlated because NO2 is a precursor to PM. While particulate matter is also directly emitted from certain pollution sources (such as road traffic), it is mostly created by secondary formation from precursor emissions such as NOx. The differential effect of wind speed on pollution concentrations is also confirmed in my data. I find that NO2 and PM concentrations are on average higher on days with low wind speeds, while O3 concentrations are lower. See Table 2 for the coefficients from regressions of the pollutants on the wind instruments (first stage regression) where low wind is defined as below average wind speed. NO2 concentrations and particulate matter concentrations are higher on days of low wind speed and one or two days after a day of low wind speed. Figure 1 graphically illustrates the relationship between wind speed and NO2 pollution by showing maps of NO2 pollution and wind speed at the postcode level for two days of low wind speed and two days of high wind speed. NO2 concentration is visibly higher in places where and at times when wind speed is low.

Outside of extreme events, wind speed is unlikely to affect health other than through its effect on air pollution. 99% of the postcode-day wind speed observations are situated below 7.3 m/s. This wind speed corresponds to a 4 on the Beaufort scale which is described as moderate breeze that raises dust and loose

[5] Simplified reaction equation: NO2 + O2 (+ solar UV-light, + heat) → NO + O3

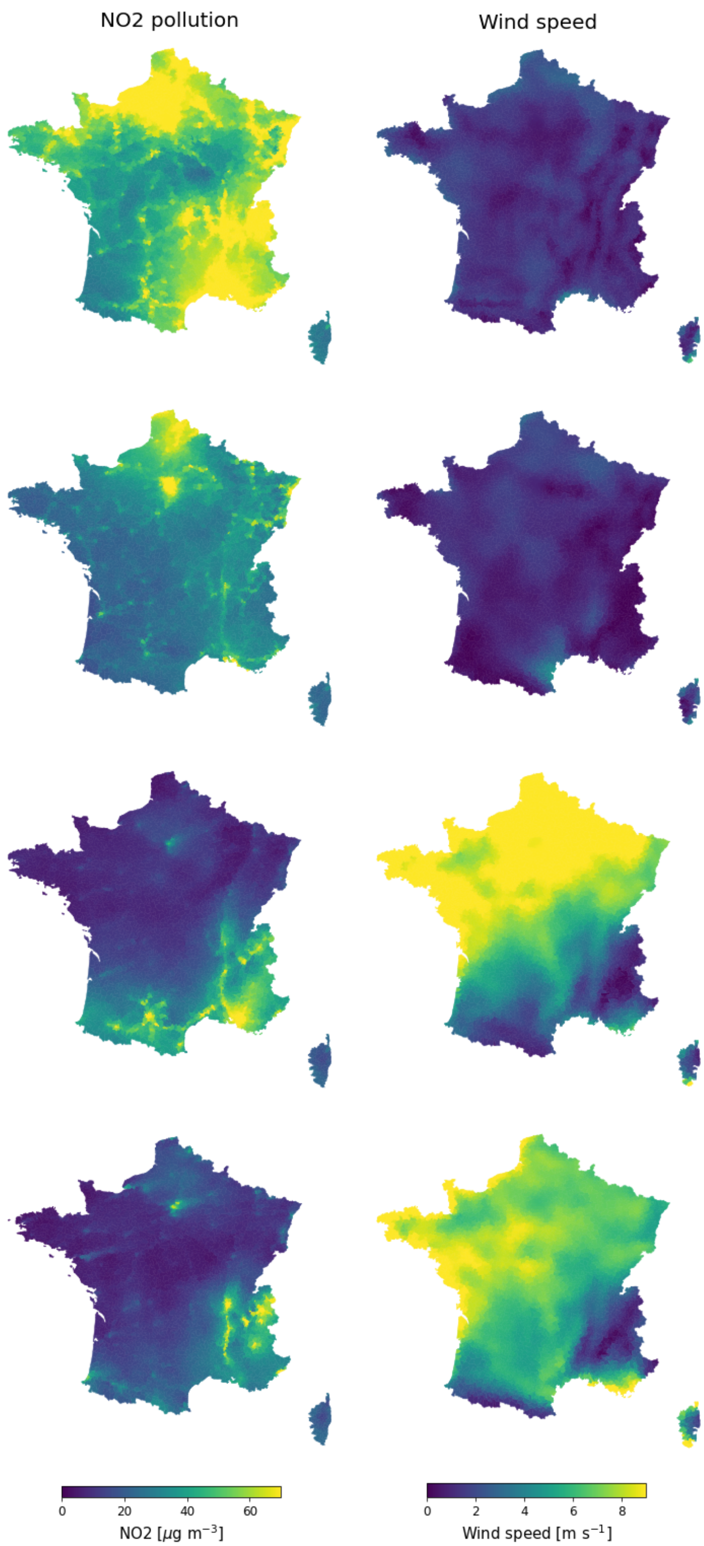

Figure 1: Level of NO2 and wind speed for two days of low wind speed (rows 1 and 2) and two days of high wind speed (rows 3 and 4).

paper and moves small branches (Royal Meteorological Society). See Table A2 in the Appendix for the all levels of the Beaufort scale, corresponding wind speeds and description of the conditions. Wind speed could vary seasonally and with temperature and other meteorological parameters which could also be correlated with healthcare use. I account for this possibility by including time fixed effects and a vector of controls for meteorological conditions.

3 Data

I combine administrative data on healthcare reimbursements with reanalysis data on pollution levels and weather conditions, as well as data on public transport strikes for France from 2015 to 2018 which I merge by day and by postcode area.[6]

3.1 Healthcare use and costs

I use administrative data on healthcare reimbursements from the French National System of Health Data (SNDS for *Système National des Données de Santè*) covering the period 2015 to 2018. The French healthcare system is based on universal coverage by one of several healthcare insurance plans. The SNDS database merges anonymous information of reimbursed claims from all these plans and is also linked to the national hospital-discharge summaries database system. The data covers 98.8% of the French population, over 66 million persons, from birth or immigration to death or emigration, making it possibly the world's largest continuous homogeneous claims database. The database provides information on the nature of medical acts and associated costs of treatment for all types of healthcare, including physician visits, drug purchases, and hospital care. The information is available by exact date of care and also includes codes for the classification of medical acts into medical specialities. Some data on patient characteristics are also available, including patient age, gender, information on chronic health conditions, and place of residence at postcode area level.

I conduct the study on a representative sample of this database, called the general sample of beneficiaries (EGB for *Echantillon Généraliste des Bénéficiaires*). This is the 1/97th random permanent representative sample of SNDS. The EGB facilitates the conduct of longitudinal studies as beneficiaries are identified through their national identification number, a unique personal identification, which allows to follow them over time. The EGB permits tracing back patients healthcare use history. See Tuppin et al. (2010) and Bezin et al. (2017) for more information on the EGB. For most analyses, I aggregate the individual-level data on healthcare use and cost by the patient's postcode area of residence. For heterogeneity analyses, I additionally group by patient characteristics.

[6]France is divided into around 6,000 postcodes.

A limitation of the SNDS is that it does not contain any direct measure of the patient's socioeconomic status (SES). However, it provides information concerning the patient's complementary insurance plan including information on whether the individual subscribed to any plan, the choice of the insurance provider and whether the individual is covered by the CMUc (*Couverture médicale universelle complémentaire*), a state funded complementary insurance plan available to low-income individuals. I use this information to approximate SES, supposing that coverage by CMUc indicates low SES.

3.2 Air pollution

I exploit reanalysis data on hourly concentrations of NO2, O3, PM10, and PM2.5 provided by the French National Institute for Industrial Environment and Risks (INERIS for *"Institut national de l'environnement industriel et des risques"*). The data comes in the form of raster files with high spatial resolution (cell size of about 4x4 km). I convert the hourly data into daily means and maximum values and superpose the raster data with a shapefile of France containing administrative boundaries at the postcode area to extract daily pollution levels by postcode area.

Reanalysis data offers substantial improvements over data from measurement stations. The number of monitoring stations is limited (for example, Figure A1 in the appendix shows a map of the spatial distribution of NO2 measuring stations in France) and can vary over space and time in a non-random order. Using data from monitoring stations implies assuming that the pollution concentration is homogeneous within a given radius around the station, potentially generating a mismatch between the true and assigned level of pollution especially for locations situated farther away from the measurement stations. In many studies, researchers interpolate data points using weights of different nature to obtain information for locations far from the monitoring stations (see for example Currie and Neidell (2005); Knittel et al. (2016); Schlenker and Walker (2015)). However, interpolating pollution levels by using simple distance weights neglects meteorological and geographical factors which influence pollution dispersion in crucial ways. The reanalysis data from INERIS combines information from measurement stations with a climate model rather than using a statistical procedure to interpolate between observations to address this issue.

3.3 Meteorological conditions

I use data on hourly wind speed, wind direction, temperature and precipitation from the ERA5 global land-surface data set which is produced by the Copernicus Climate Change Service (C3S) at the European Centre for Medium-Range Weather Forecasts (ECMWF). This is the fifth generation of the ECMWF atmospheric reanalysis of the global climate. The data is freely available online at `https://cds.climate.copernicus.`

eu/cdsapp#!/dataset/reanalysis-era5-land?tab=overview. These data are in the form of raster files with a spatial resolution of 9x9 km. I convert the data into daily averages and overlay the raster data with a shapefile of France containing the administrative boundaries at postcode level to obtain the data per postcode area.

Reanalysis combines model data with past observations from measurement stations into a globally complete and consistent dataset using the laws of physics. This offers improvements over using data from measurement stations because using such data usually implies assuming that the level of the measured variable is homogeneous within a given radius around the station. This potentially generates a mismatch between the true and assigned level of the variable especially for locations situated farther away from the measurement stations.

3.4 Additional data

I use additional data on postcode-level average household income, Gini Index (measure of income inequality ranging from 0 to 1, 1 being most unequal), and unemployment rate from the Localized Social and Fiscal File (FiLoSoFi for *Fichier Localis Social et Fiscal* in French) provided by the French National Institute of Statistics and Economic Studies (INSEE for Institut national de la statistique et des études économiques in French). This database generally includes income distribution indicators reported by households, for all households and by household category and is publicly available online from the website https://www.insee.fr/fr/metadonnees/source/serie/s1172. Additional data on holidays in France are obtained from https://www.data.gouv.fr/en/datasets/jours-feries-en-france.

In an extension of this work, I also consider public transport sector strikes as instrument for air pollution levels. For this, I manually collected information on the dates and locations of public transport strikes through Google searches and from the website https://www.cestlagreve.fr/. I consider any strike affecting train, tram, metro or bus services. Based on the collected data, I construct an indicator variable equal to one when a particular post code area was affected by public transport strikes at any given day. I also construct the distance in km between the postcode area centroid to the nearest location of strike to look at potential spillover effects of strikes in nearby locations. I construct similar indicator variables for strikes at the department and national level. Finally, I obtained data on the percentage of agents at the French National Railway Company (SNCF for *"Socité nationale des chemins de fer français"*) who followed the call to strike during national strike movements as measure of strike intensity. This data is available at https://ressources.data.sncf.com/.

3.5 Summary statistics

Table A3 in the appendix presents summary statistics for the entire sample consisting of 8,835,995 postcode-day observations. I run several regressions on a sub-sample comprising the 10% most densely populated postcode areas and another sub-sample comprising only the postcode areas that make up the 70 largest French cities (about 2% of the sample). The summary statistics for these samples are presented in Tables A4 and A5 in the appendix. In the whole sample, the daily average healthcare expenditure is 513.76 Euros with a standard deviation of 1415.4. Mean daily concentration of NO2 is 13.8 (standard deviation 8.44); concentration of PM 10 is 16.61 (sd 8.47); concentrations of of PM 2.5 is 10.58 (sd 7.44) and concentrations of O3 is 55.64 (sd 20.32) micrograms per cubic meter. Average NO2 and PM pollution levels are higher and O3 levels are lower in the reduced samples which should be unsurprising as these include mostly observations in urban areas[7]. Average spending is higher in the reduced samples. Postcode, department and/or national level public transport sector strikes are happening in around 30% of the postcode-day observations.

Pollution concentrations in France are generally situated below the limit value that is considered safe for human health. This can be seen from Figure 2 which displays the distribution of daily maximum hourly and daily mean pollutant concentration together with the corresponding limit value. Figure 3 presents box plots showing how health expenditure and pollutants vary by day of the week and month, indicating cyclical changes over the week and seasons.

[7]Note that NO2 and PM are negatively correlated with O3 as discussed in section 2.

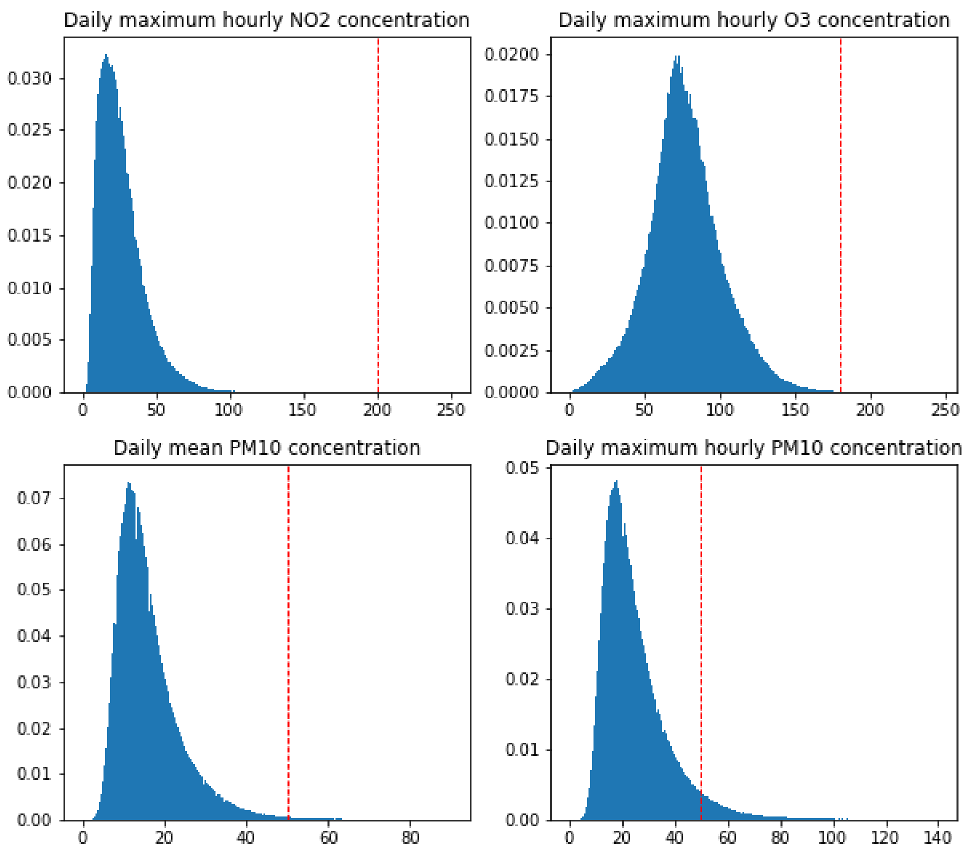

Figure 2: Level of pollutants relative to the limit values presented in Table A1.

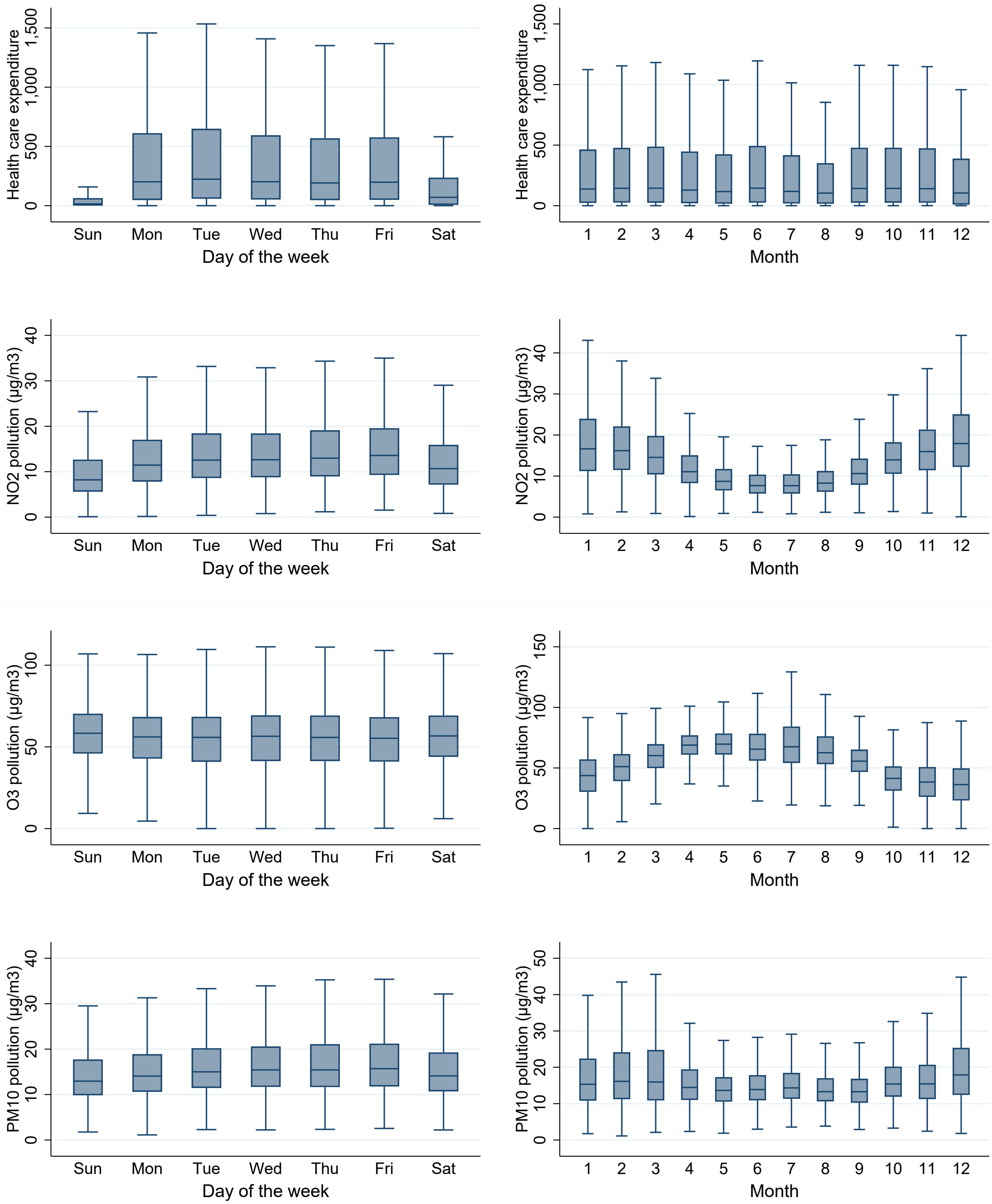

Figure 3: Mean of healthcare expenditure and pollutants by day of the week and month. The lower and upper edges of the box show the 25th and 75th percentile, the bar in the box shows the median value. The whisker The length of the upper whisker is the largest value that is no greater than the third quartile plus 1.5 times the interquartile range. The lower whisker is defined analogously.

4 Method

4.1 Location and time fixed effects model

The objective is to estimate the causal short-run effect of exposure to air pollution on healthcare use and costs. Exploiting daily variation in the intensity of air pollution at the postcode area level, I estimate the following model:

$$H_{dpc} = \beta P_{dp} + \alpha_p + \alpha_{dow} + \alpha_{mdep} + \alpha_{y/my} + \gamma X_{pd} + \epsilon_{xdp}, \tag{1}$$

where H_{dpc} denotes healthcare use or cost on day d in postcode area p and for medical speciality c. I regress this on a vector of pollution concentrations P_{dp} on day d in postcode area p. In my preferred specifications, I include either NO2 or PM together with ozone to account for correlations between these pollutants and the fact that they are likely to have independent effects on health. NO2 and particulate matter are positively correlated and inversely related to O3 because NO2 is a precursor to PM and NO2 (generally NOx) and O3 are linked through equilibrium reactions (see again section 2). I further discuss issues related to the correlation between the pollutants and show results for models with different vectors of pollution in the next section.

Individuals can spatially sort according to preferences and characteristics that can be correlated with both their health status and their level of exposure to pollution. I control for location fixed effects at the level of the postcode area α_p to account for the possibility that unobserved site characteristics are correlated with both average pollution levels and average healthcare use. I also flexibly control for seasonality in air pollution and healthcare use by including a range of time fixed effects. I include day-of-week (α_{dow}), month-by-department (α_{mdep}), and month-by-year (α_{my}) fixed effects. Month-by-department fixed effects flexibly control for any seasonal correlation between pollution and health that are allowed to vary by department.[8] The month-by-year fixed effects control for common time-varying shocks, such as changes in environmental policy.

I denote X_{pd} the vector of additional time-varying covariates which include variable indicating holidays and indicator variables for daily mean temperatures and daily precipitation falling into 10 bins by decile and different possible interactions of these weather indicator variables. In robustness checks, I try out alternative model specifications with different more or less flexible time fixed effect structures and weather controls. In some specifications, I include up to three lags of the air pollutants and weather variables to consider the

[8]France is divided administratively into 95 departments which are smaller than the regions, of which there are 18, but much larger than the communes which are analogous to the civil townships and incorporated municipalities in the United States and Canada. There are over $34,000$ communes in France that are are served by around 6,000 postcodes.

possibility that pollution build-up over the past days may impact health outcomes.

Standard errors are clustered at the postcode level. The results are robust to different clustering choices, including clustering at the postcode are or the employment zone level.

4.2 Wind speed as instruments for air pollution

Both air pollution levels and healthcare use change cyclically throughout the week (see Figure 3) and appear to be correlated with economic activity. The sign of the bias is in theory ambiguous. Day to day variation in the supply of healthcare (in terms of opening hours or generally the availability of physicians) is likely to drive healthcare spending and positively correlates both with economic activity and pollution levels. In this case, the estimate of the effect of air pollution on healthcare spending could be upward biased. Alternatively, daily changes in healthcare demand could be negatively correlated with economic activity (no time to go to the doctor when on the job) which is positively correlated with pollution levels. In such a case, the effect of pollution on healthcare spending could underestimated. A possible cause for concern is that the fixed effect structure in equation (1) does not correctly purge these effects. This could be the case, for example, if the day-of-week fixed effects common to all postcode areas do not correctly capture the co-movements between pollution, economic activity and healthcare provision. In robustness checks, I investigate this possibility by estimating models including day-of-week by postcode fixed effects. To address endogeneity issues more generally, I estimate instrumental variable (IV) models in which I use wind speed as instrument for air pollution. Wind speed is plausibly exogenous to economic activity, which means that the IV approach allows me to estimate the effects of air pollution on healthcare use and costs without accidentally capturing correlations due to economic activity.

A valid instrumental variables approach requires that the instruments (i) be sufficiently correlated with the endogenous variable of interest and (ii) not be correlated with any unobserved determinants of the outcome of interest (exclusion restriction). In the present case this means that wind speed must be sufficiently correlated with air pollution and it must affect healthcare use only through its influence on pollution levels. I find that pollution levels are indeed correlated with wind speed. NO2 and PM10 concentrations are higher on days with low wind speed, as these pollutants are carried away from their source of origin on days of high wind speed. O3 is higher on days of high wind speed due to its inverse relationship with NO2 and the fact that NO2 is higher on such days. See Section 2 of this paper for more information. It is plausible that the exclusion restriction holds. Common levels of wind speed are unlikely to have a direct effect on healthcare use. Extremely high wind speed could potentially increase healthcare use due to a higher risk of accidents but not due to pollution exposure because pollution levels are lower on days of high wind speeds. Wind speed could vary seasonally and with temperature and other meteorological parameters which could also be correlated with healthcare use. I account for this possibility by including time fixed effects and a vector of controls for meteorological conditions.

Formally, the first stage specification is as follows:

$$P_{xdp} = \beta_0 IV_{dp} + \alpha_p + \alpha_{dow} + \alpha_{mdep} + \alpha_{y/my} + \delta X_{pd} + \epsilon_{xdp} \quad (2)$$

where P_{xdp} denotes the measure of pollution of pollutant x on day d in postcode area p, IV_{dp} is a vector of wind speed instruments including either wind speed, wind speed squared and lags or indicator variable equal to one if wind speed is below average on day d in post code area p and zero otherwise and the lags of this indicator variable. The control variables and the fixed effects are the same as in equation 1.

The data are very detailed which allows me to thoroughly explore treatment effect heterogeneity. I study heterogeneous effects across a range of patient characteristics such as age, sex, chronic disease status as well as postcode area characteristics including postcode-level average income, Gini Index and unemployment rate. I hypothesise that children and the elderly, people with chronic diseases and those living in poorer, more unequal and higher unemployment areas are more strongly affected by air pollution exposure.

5 Results

5.1 Main results

Table 1 reports the main estimates of the relationship between daily nitrogen dioxide (NO2) and ground-level ozone (O3) pollution and overall healthcare costs. Column 1 shows that each 1 $\mu g/m^3$ increase in daily NO2 (about 7.2% of the mean) is associated with 5.59 € of additional healthcare expenditure the same day which corresponds to a 1.1% increase relative to the average daily healthcare spending. Each 1 $\mu g/m^3$ increase in daily O3 (about 1.8% of the mean) increases spending by 0.79 € or 0.2% relative to the average daily spending. Column 2 and 4 present the corresponding IV estimates where NO2 and O3 pollution are simultaneously instrumented for with dummy variables equal to 1 if local wind speed is below average on a given day, the previous day, two days previously. The estimates from the model using this wind speed IV imply that each 1 $\mu g/m^3$ increase in daily NO2 causes an increase of 7.57 € in aggregate healthcare spending whereas each each 1 $\mu g/m^3$ in daily O3 causes an increase of 3.94 € which translates to an increase of 1.5% and 0.8% relative to the average daily spending. The IV estimates are larger than the OLS estimates, suggesting that OLS estimation is biased downward and that endogeneity problems may persist despite using high-frequency data.

Table 1: OLS and IV estimates of effect of NO2 and O3 on healthcare expenditure

	Health spending Entire France		Health spending 70 biggest cities	
	OLS (1)	Wind IV (2)	OLS (3)	Wind IV (4)
NO2 mean	5.59***	7.57***	15.08***	24.83**
	(0.382)	(1.240)	(2.405)	(9.480)
Effect relative to mean (%)	1.1	1.5	0.4	0.7
O3 mean	0.79***	3.94***	5.07***	22.10**
	(0.057)	(0.591)	(0.711)	(7.566)
Effect relative to mean (%)	0.2	0.8	0.1	0.6
Dependent variable mean	513.76	513.76	3550.96	3550.96
Observations	8495951	8484329	215497	215203
First-stage F-stat		8805.0		551.1

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects. Air pollution is simultaneously instrumented for with dummy variables equal to 1 if local wind speed is below average on a given day, the previous day, two days previously. The sample of the 70 biggest cities corresponds to 2% of the entire sample.

The effects are larger when I restrict the sample to include only the most populated areas. Columns 3 and 4 report the estimates from regressions using a sample of the France's 70 biggest cities which corresponds to 2% of the whole sample. The estimates are about 2.5 to 6.5 times bigger than the estimates from the regression on the whole sample. Different samples selected according to total population or population density yield qualitatively similar results. For example, Table A6 in the appendix shows the results for a sample of the 10% most populated postcode areas where the estimates are larger than the estimates for the whole sample but smaller than the results for the sample of 70 biggest cities[9]. This suggests that the effects of pollution are concentrated in urban areas, potentially due to non-linear effects of pollution. A 1 $\mu g/m^3$ increase in pollution in an area with higher average pollution levels could have larger effects on health relative to the same increase in pollution in an areas with lower average pollution levels. I further investigate the existence of such non-linear effects in the heterogeneity analyses presented in the next subsection.

I include O3 together with either NO2 or PM to avoid underestimating the effects of any pollutant because I observe important correlations between the pollutants. NO2 and particulate matter are positively correlated and inversely related to O3. The reason for these correlations is that NO2 is a precursor of particulate matter and NO2, or more generally NOx, and O3 are linked by equilibrium reactions (see Section 2 for details). Failure to account for these co-movements risks to introduce bias in the estimates. Consider the example of an increase in NO2 or PM which may have adverse health effects, but which coincides with a decrease

[9] I run several regressions on a sub-sample comprising the 10% most densely populated postcode areas and another sub-sample comprising only the postcode areas that make up the 70 largest French cities (about 2% of the sample). The summary statistics for these samples are presented in Tables A4 and A5 in the appendix.

in O3 which may have beneficial health effects offsetting the effects of the increased NO2 or PM. Ignoring the effect of O3 may lead to an underestimation of the effects of NO2 or PM. I find that it is important to account for the correlations between the pollutants. The results are not robust if only one pollutant is included without simultaneously instrumenting or at least monitoring the other observed pollutants. See Table A7 for the estimates considering only one pollutant at a time.

Most of the variation in air pollution comes from variation in NO2 and O3. The effects of NO2 and O3 are robust to the inclusion of particulate matter as additional control variable. Panel A of Table A8 in the appendix shows that the results remain qualitatively the same. The results for particulate matter pollution are less robust. When I focus the analysis on the effects of particulate matter and O3 pollution while adding NO2 pollution only as additional control, I find that particulate matter pollution increases healthcare spending but the effects are far less pronounced than the effects from NO2 pollution. See Panel B of Table A8 in the appendix. The results are not robust when I focus the analysis on the effects of particulate matter and O3 pollution without controlling for NO2. However, it may not be very meaningful to separate the effect of the two pollutants because NO2 is a precursor to PM and some of the health effects of NO2 are also potentially mediated through the health effects of PM. Using pollution indexes to simplify the analysis did not yield significant results, likely because using such indexes result in a large loss of information. Pollution indexes are usually constructed by classifying pollution concentrations into categories according to their harmfulness to health, and then taking the maximum of the index among the pollutants considered. The index could potentially not change despite significant changes in NO2 and O3 concentrations, as long as one compensates for the other. In addition, the construction of the index requires assumptions to be made about the relative harmfulness of the different pollutants.

The first stage F-statistics, reported at the bottom of Table 1, are generally large, suggesting that there is no problem of weak instruments. Tables 2 shows the first stage regressions for the whole sample the small sample of the 70 biggest cities.

The results are generally robust to the inclusion of different time fixed effects vectors and different first stage specifications including different lag structures of the wind instrument dummy variable as well as using absolute wind speed and lags of absolute wind speed as instrument. The results are robust to clustering at the level of the postcode area and at the more aggregate level of the employment zone. See Section 6.1 presenting robustness checks.

Table 2: First stage regressions corresponding to the IV regressions shown in Table 1

	First stage - entire France			First stage - 70 biggest cities		
	NO2 mean	O3 mean	PM 10 mean	NO2 mean	O3 mean	PM 10 mean
Low wind speed	3.747***	-7.264***	1.973***	7.131***	-8.136***	3.193***
	(0.026)	(0.025)	(0.018)	(0.177)	(0.201)	(0.108)
Low wind speed Lag 1	1.526***	-4.300***	1.940***	2.488***	-4.708***	2.699***
	(0.012)	(0.017)	(0.017)	(0.091)	(0.124)	(0.099)
Low wind speed Lag 2	0.294***	-1.315***	0.943***	0.125***	-1.306***	1.069***
	(0.004)	(0.012)	(0.008)	(0.029)	(0.081)	(0.044)
Observations	8484454	8484454	8484454	215203	215203	215203

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

5.2 Results by location characteristics

This section presents the results of the heterogeneity analyses by postcode area characteristics. I separate postcode areas into quantiles according to average household income, unemployment rate, average pollution levels, and population size. Figure A2 in the appendix present box plots of per capita healthcare spending by postcode area characteristics deciles. Per capita healthcare spending is higher in areas with higher average NO2 pollution and more populated postcode areas whereas there are no clear differences by postcode area average income and unemployment rate.

This pattern is also confirmed by the regression results. Regressions run separately by postcode characteristic quartiles as shown in Table A9 in the appendix point to stronger effects in areas with higher average household income, lower unemployment rate, higher average pollution levels and larger population size. However, the postcode characteristics are correlated. Average household income, unemployment rates, and average pollution levels are higher in areas with larger population size which corresponds to postcode areas in the city. To examine which of the location characteristics drives the effect heterogeneity, I include the postcode characteristics together in one regression by interacting pollution or the instruments with the postcode characteristics quartiles. I find that the dimension that matters are population size and average NO2 pollution levels. The coefficients on the interactions with average income and unemployment quartiles are not statistically significant anymore once the quartiles for population size or average pollution level are included.

5.3 Results by patient characteristics

Many of the existing studies on the health effect of air pollution focus on the young or elderly populations as these populations are generally considered to be the most vulnerable. I find evidence of effects across all age categories, suggesting that adverse health effects also manifest in parts of the population that are less often considered. Table A10 in the appendix shows OLS and IV model results for regressions run separately for 10-year age groups. The estimated level effect is higher for older individuals of 40 years and above, but the effect relative to the age group's average expenditure is more similar across age groups. A potential explanation for this is that many of the previous studies focus on the effects of mortality, which is a rather extreme outcome likely to affect the only the most vulnerable populations. I look at overall healthcare costs, which include the costs of treating milder health consequences that are likely to occur in all age groups.

I further explore whether individuals with preexisting health conditions or low-socioeconomic status individuals are more vulnerable to pollution exposure. Table A11 in the appendix shows the results for regressions run separately by chronic disease and socioeconomic status. As I do not have direct information on socioeconomic status, I investigate heterogeneity by socioeconomic status supposing that insurance coverage by the CMUc (*Couverture mdicale universelle complmentaire*), a state funded complementary insurance plan available to low-income individuals, indicates low socioeconomic status. I find that the effects of NO2 and O3 pollution are in between 1.2 to 4.8 times larger in the population suffering from a chronic disease. I find some limited evidence that low-socioeconomic status individuals are more strongly affected. The OLS regressions suggest stronger effects for these individuals enrolled in the CMUc (proxy for low-socioeconomic status) with respect to the group's average spending, but the IV estimates are imprecisely estimated.

5.4 Results by medical speciality

I examine what types of health conditions are affected by exposure to air pollution by running separate regressions for 15 different categories of medical specialities. While interesting in its own right, this exercise also serves as a sanity check. I consider both medical specialities that should be affected by air pollution and medical specialities that should not be affected as placebos. Among the categories that I expect to be affected are family practice (primary care physician), otorhinolaryngology, ophthalmology, stomatology, dentistry, cardiology and vascular medicine, pulmonology, neurology, genecology, abmulance services. The placebo specialities include gastro-hepatology, rhumatology, nephrology and plastic surgery.

Table A12 in the appendix shows the OLS results by medical speciality. In Panel A, all estimates, including the coefficients on the placebo categories, are positive and statistically significant. This suggests that problems of endogeneity may remain even in high frequency data and using location and time fixed effects models. Probably, the structure of the time fixed effects does not adequately capture the co-movements of pollution and healthcare activity related to economic activity. For example, changes in the demand and supply of medical services due to economic activity that are correlated with but not caused by changes in pollution could differ across locations in a way that day-of-the-week fixed effects common to all locations cannot explain. This hypothesis is supported by the results from regressions where I interact a dummy variable indicating that the day is a weekday with the postcode area fixed effect to allow the weekly cyclical movements to vary by postcode area. These results are reported in Panel B of Table A12. I find that most the coefficients on the placebo medical categories are now less statistically significant or not significant anymore.

Results by medical speciality for the model using wind as instrument for air pollution are reported in Table A13 in the appendix. The wind IV appears to address the problem of endogeneity as the coefficients on the placebo categories are much smaller and not statistically significant. In fact, only the estimates for family medicine and ambulance services are statistically significant. The wind IV approach seems therefore to be conservative. See also Section 6 where I analyse effects by medical speciality using public transport sector strikes as alternative instrument for air pollution.

6 Sensitivity analyses and extensions

6.1 Robustness to different fixed effect structures and weather controls

Table A14 in the appendix shows the main OLS and IV estimates of the relationship between daily NO2 and O3 pollution and healthcare costs with different fixed effects structures and additional controls. Columns 1 to 6 show results for models with a simpler time fixed effect structure, including month and year fixed effects rather than month-by-department and month-by-year fixed effects. Columns 3 and 4 additionally exclude the vector of weather controls while columns 5 and 6 additionally exclude day of the week fixed effects. The results are generally robust to including simpler time fixed effects as long as day-of-the-week fixed effects are included. Failing to account for cyclical movements in pollution and healthcare use by excluding the day-of-the-week fixed effects yields significantly larger coefficients. Including additional controls for pollution and weather lags yields also larger estimates as shown in columns 7 and 8. The results from the preferred specification reported in the main table are therefore comparatively conservative. Table A15 in the appendix shows that the results are qualitatively similar when using different definitions of the wind IV, including more or less lags of the dummy indicating below average wind speed (columns 1 and 2) and using absolute wind speed and lags of absolute wind speed (columns 3 and 4).

6.2 Analysis at the level of the employment zone

In my empirical strategy, I assume that the postcode area of residence corresponds to the location of exposure to air pollution. However, people are also exposed to air pollution at their place of work, place of leisure or while commuting. The postcode area is a relatively small geographical unit and it is quite likely that the postcode area of residence does not correspond to the postcode area of work. If this leads to a large measurement error in pollution exposure, my estimates could be biased towards zero (attenuation bias). I check whether the results are robust to conducting the analysis at a higher level of spatial aggregation by running the analyses at the employment zone level. The employment zone (*"zone d'emploi"* in French) is a division of the French territory into geographical areas within which most of the working population resides and works.[10] There are 306 employment zones in France. See Figure A3 in the appendix. The results hold when the analysis is conducted at the employment zone level as can be seen in Table A16 in the appendix. The effects of NO2 and O3 on healthcare spending remain qualitatively the same.

6.3 Effects of air pollution on sick leave and mortality

I further explore the effect of air pollution on sick leave spending and mortality. The results are shown in Table A17 in the appendix. An increase in NO2 and O3 pollution leads to an increase in costs for the healthcare system due to sick leave payments. The results regarding mortality are not conclusive. I find a small effect on mortality using the OLS model, but the results for the IV regressions are not statistically significant. It is possible that air pollution does not lead to a significant increase in same-day mortality. However, I also do not find results in models where I allow the effect of pollution to impact mortality with some lag. I may not have the statistical power to accurately estimate mortality effects, as the representative sample of the French population I use probably includes an insufficient number of observations of individuals from the most affected groups. To estimate effects of air pollution on three-day mortality, Deryugina et al. (2019) use data on the entire population of US elderly.

6.4 Wind direction, thermal inversions, and public sector transport strikes as alternative instruments

I explore the use of wind direction and thermal inversions as other potential instruments for air pollution. The wind direction instrument should capture the variation in pollution due to the transport of non-local pollution while the wind speed instrument instead captures variation in local pollution emissions. I interact dummies for the daily average wind direction by 90-degree intervals with a dummy for the postcode area to

[10]See the definition by INSEE here: `https://www.insee.fr/fr/metadonnees/definition/c1361`.

allow the wind direction instrument to vary by location. This is very similar to the IV specification used by Deryugina et al. (2019). Thermal inversions are a weather phenomenons known to affect pollution levels. Thermal inversions are a deviation from the normal monotonic relationship between air temperature and altitude which occur in the lower troposphere (below an altitude of around 4 km). Under normal atmospheric conditions, warm air at the surface is drawn upwards as a result of its lower density. This atmospheric ventilation can help to reduce pollution levels at the surface. During a thermal inversion, however, the inversion layer prevents the normal atmospheric ventilation from taking place, trapping polluted air at the surface. This effect is widely known and documented in the scientific literature (Wallace and Kanaroglou, 2009; Gramsch et al., 2014). I follow Dechezleprêtre et al. (2019) in defining an indicator variable of thermal inversion equal to 1 if the daily average temperature is higher at the second lowest level of the atmosphere than at the lowest level above the surface. Results are presented in Table A18 in the appendix. Using the wind direction IV yields larger coefficients. Using thermal inversions as instrument yields results that are qualitatively similar but that are not always robust to different model specifications.

For the analyses by medical specialties, I also consider strike periods in the public transport sector as instrument for air pollution. The exclusion restriction for this instrument should hold for some selected medical specialties such as cardio-vascular and respiratory care which I analyse separately from other medical specialties that could be affected by the occurrence of strikes, such as for example trauma surgery due to changes in road traffic accidents. It has been shown that road traffic volume and travel times increase on days of public transport strikes as many travellers switch to cars. Several studies also established correlations between periods of strike and increases in air pollution (van Exel and Rietveld, 2001; Bauernschuster et al., 2017; Basagaña et al., 2018; Godzinski and Suarez Castillo, 2019). Increased air pollution following increased road traffic is to be expected. In Europe, road traffic is estimated to be responsible for around 28% of the total emissions of nitrogen oxides (NOx) which are precursor emissions to both particulate matter and ground-level ozone. Although road transport only accounts for 2.88% and 5.39% of primary PM 10 and PM 2.5 emissions, it is estimated that traffic contributes for up to 30% of total particulate emissions (primary and secondary PM) in European cities. Ground-level ozone is a secondary pollutant which is not directly emitted by traffic but formed by the influence of solar radiation from the precursors NOx and volatile organic compounds (VOC). Traffic is the main source ($> 50\%$) of these ozone precursors (IRCEL, 2020). Public transport in France is generally well developed and account for 19.4% of all passenger-kilometers travelled in France in 2018. Aside the well equipped Paris area, other regions count 11 metro lines, 65 tramways (in 2017) and over 3691 bus lines (in 2012) (Commissariat général au développement durable, 2015, 2020). Public transport strikes are therefore likely to affect an important part of the French population, especially individuals living in urban areas.

In my data, I find that daily NO2 and PM10 concentrations increase on days of public transport sector strikes whereas O3 concentrations decrease (first stage regression results shown in Table A19 in the appendix). The relation between public transport strikes and particulate matter pollution is unclear. I see an decrease in particle pollution on the first day of the strike, but an increase on the second day. The lack of a clear relationship between PM and periods of strike is not entirely surprising. PM is mostly created by secondary formation from precursor emissions, meaning that the link between PM and road traffic emissions is mostly indirect. The results by medical specialty using strike as instrument for air pollution are reported in Table A20 in the appendix. Strike IV appears to partially solve the endogeneity problem that seems to be behind the positive and statistically significant coefficients for placebo medical specialties in the OLS regressions (see Section 5.4). The coefficients on the placebo categories rhumatology, nephrology, and gastrohepatology are not statistically significant. The coefficient on plastic surgery is statistically significant at the 5% level, but this effect disappears in models where I interact weekday and postcode area fixed effects. I find the results for the categories otorhinolaryngology, ophthalmology, dentistry, neurology, genecology, and abmulance services. These are categories that I expected to be influenced by pollution exposure, but that appear unaffected when using wind speed as IV. Using strike as IV for pollution yields stronger results compared to models using wind speed as IV. However, these results could be driven by violations of the exclusion restriction. The positive and statistically significant estimate on trauma surgery points toward important limitations public transport strikes as IV for air pollution. Trauma surgery is very likely unrelated to pollution exposure. The positive and significant coefficient could stems from a direct effect of strike on trauma surgery expenses, potentially through an increased number of accidents due to increased car traffic. In a similar manner, finding no effects on spending for respiratory diseases (pulmonology) could also be due to a violation of the exclusion restriction. It has been shown by Adda (2016) that the transmission rates of infectious diseases decreases during public transportation strikes in France. Such a direct effect of the strike could counterbalance a potential increase in the costs of air pollution-induced respiratory diseases. These results suggest that the use of wind speed or, in general, atmospheric conditions is preferable to the use of public transport strikes or similar shocks to road traffic for assessing the causal effects of air pollution on healthcare use and costs.

7 Discussion

This study presents evidence of non-negligible healthcare costs caused by exposure to pollution levels that are mostly below current legal limits. I estimate that each 1 $\mu g/m^3$ increase in daily NO2 (7.2% of the mean) cause an increase of €7.57 in aggregate healthcare spending whereas each each 1 $\mu g/m^3$ in daily O3

(1.8% of the mean) causes an increase of €3.94 which translates to an increase of 1.5% and 0.8% relative to the average daily spending. These are relatively conservative estimates, as many model specifications result in even larger estimates. The estimates in this study reflect the costs of acute (short-term) exposure to air pollution while the potentially even larger effects of long-term exposure are not considered. Yet the high costs from short-term exposure alone suggest that there are considerable benefits to reducing air pollution, as the following back-of-the-envelope calculation illustrates.

7.1 Back-of-the-envelope cost-benefit analysis

The increase of €7.57 per day per postcode for a 1 $\mu g/m^3$ increase in daily NO2 results in €1.6 billion additional healthcare spending per year. Adding the effect for a 1 $\mu g/m^3$ increase in daily O3 amounts to €2.5 billion of additional spending per year.[11] To obtain these numbers, I assume that the daily effects of a 1 $\mu g/m^3$ increase in daily pollutant concentrations can be scaled linearly to yearly effects of a 1 $\mu g/m^3$ increase in annual average pollutant concentrations. This is a conservative approach as in the epidemiological literature the long-term health effects of air pollution exposure are generally considered more important than the short-term effects.

Compliance with the National Emission Commitment (NEC) Directive (2016/2284/EU)[12] requires France to reduce nitrogen oxides (NOx, composed of both NO2 and NO) by 50% compared to 2005 values, to be achieved from 2030. In 2005, annual NO2 concentrations in France were 17.5 $\mu g/m^3$[13], which means that France should reduce NO2 by 8.75 $\mu g/m^3$ until 2030. Given the 2017 average of 12.01 $\mu g/m^3$[14], this implies a further decrease of 3.26 $\mu g/m^3$ of annual NO2 concentration which, which I estimate will result in an annual saving of €5.2 billion in healthcare costs when France meets its commitment. This contrasts with the €9.9 billion annual costs of compliance with the NEC Directive as estimated in Amann et al. (2017). The short-term benefits from a reduction in healthcare costs due to the decreased NO2 pollution alone sets off more than 50% of the total costs of compliance with the NEC directive.

[11] The €7.57 increase per day per postcode for a total of 6,048 postcodes and in a sample the size of 1/97 of the total French population translates into $€7.57 \cdot 97 \cdot 365 \cdot 6,048 = €1,620,959,861$ healthcare spending per year. Similarly, the €3.94 increase in spending related to a 1 $\mu g/m^3$ increase in daily O3 translates into $€3.94 \cdot 97 \cdot 365 \cdot 6,048 = €843,669,994$ healthcare spending per year.

[12] Directive (EU) 2016/2284 of the European Parliament and of the Council of 14 December 2016 on the reduction of national emissions of certain atmospheric pollutants, amending Directive 2003/35/EC and repealing Directive 2001/81, https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32016L2284&from=EN

[13] 20 ans d'évolution de la qualité de l'air cartographiés par l'Ineris, https://www.ineris.fr/fr/recherche-appui/risques-chroniques/mesure-prevision-qualite-air/20-ans-evolution-qualite-air

[14] Ibid.

7.2 Comparison of the effect size with results from previous studies

Most studies that seek to evaluate the health costs of air pollution for cost-benefit analysis estimate the costs indirectly through simulations based on air quality and population data, baseline rates of mortality and morbidity, concentration-response parameters from the epidemiological literature, and unit economic values. Often, only a selection of health effects for which epidemiological evidence is most robust are included in these models. For example, the Environmental Benefits Mapping and Analysis ProgramCommunity Edition (BenMAP-CE) is a tool historically used by the Environmental Protection Agency (EPA) but also widely employed by other agencies and researchers to estimate the economic impact of a range of clinical outcomes due to air pollution. The model's default features consider only the costs of hospital and emergency department admissions. A more complete accounting of the chain of costs would include ambulatory and other care (including physician and clinic visits, prescription drugs, supplies, and home healthcare) that may also increase as a result of increased air pollution. When an additional quantification of such ambulatory care is added, only a subset of health effects have been considered (for example Birnbaum et al. (2020) who consider only two disease categories, respiratory and all cardiovascular disease).

I am not aware of any other study that comprehensively quantifies healthcare costs in France. The evaluation of healthcare costs caused by air pollution has so far been only very partial, resulting in a severe underestimation of costs. To inform policy decisions, a 2015 Senate Committee of Inquiry into the economic and financial cost of air pollution[15] searched for estimates of the total costs of air pollution to the French healthcare system. The result was a report on two studies that considered only a fraction of the total healthcare costs and a recommendation that more research be conducted in this area. The first of these studies is a 2007 impact study on the costs to health insurance that was conducted by the French Agency for Environmental and Occupational Health Safety (Fontaine et al., 2007). As sufficient health and economic data were not available for all air pollution-related diseases, the study only considered asthma and cancer. The estimate of the overall cost of asthma and cancer treatments attributable to air pollution was situated between 0.3 and 1.3 billion euros. The second study dates from 2015 and was carried out by the General Commission for Sustainable Development and sought to assess as comprehensively as possible the cost of air pollution to the French healthcare system (Rafenberg, 2015). However, the study only covers a selection of pathologies (cost of treatment of respiratory diseases (asthma, acute bronchitis, chronic bronchitis, chronic obstructive pulmonary disease), respiratory cancers, and hospitalisations for respiratory and cardiovascular causes related to ambient air pollution). The study arrives at an overall cost of between 0.9 billion euros and 1.8 billion euros per year which is smaller than my estimate of the effects of a 1 $\mu g/m^3$ change in

[15] In French the "Commission d'enqute sur le cot conomique et financier de la pollution de l'air". `http://www.senat.fr/rap/r14-610-1/r14-610-11.pdf`

air pollution levels. In addition, these studies estimate the healthcare costs with great uncertainty as they apply an estimate of the fraction of these diseases that is attributable to air pollution (relative to the total incidence) and then multiply the number of disease incidence by an average of the expected treatment costs.

The report by Amann et al. (2017) discussed above also includes an estimation of healthcare costs linked to air pollution which is estimated at €4.7 billion per year for the scenario of 2005 pollution levels and €2.4 billion per year for the scenario of compliance with the National Emission Reduction Commitments Directive *for the European Union (EU28) as a whole*. The benefit in terms of reduced healthcare costs at EU level is therefore estimated at only €2.3 billion per year which is much smaller than the benefits that I estimate for France alone. The total reduction in NO2 concentrations by 8.75 $\mu g/m^3$ from 2005 pollution levels should allow savings of €14 billion annually in France alone.[16] The healthcare costs are estimated by using dose response estimates from the epidemiological literature for a selection of health effects for which evidence has been conclusive. Emerging evidence on a number of possible additional health impacts that could have major added costs such as dementia, diabetes and obesity are not considered. It is therefore not surprising that the health effects estimated in Amann et al. (2017) are much smaller than the effects presented in the present study. In a study relying similarly on dose response estimates, Pimpin et al. (2018) estimate that a 1 $\mu g/m^3$ reduction in population exposure to PM2.5 and NO2 would result in 1.42 billion and 353.3 million avoided, respectively, in NHS and social care costs between 2017 and 2035. This corresponds to a saving of only 98.5 million per year in a population of comparable size to that of France (the UK population is 66.65 million compared to 67.06 million in France in 2019). This is again much lower than the estimated effects in the present study. Again, the costs are likely underestimated because only a limited number of health conditions have been considered (asthma, COPD, coronary heart disease, stroke, type 2 diabetes, dementia and lung cancer).

While these studies clearly state that the healthcare cost estimates are conservative, the extent to which total effects have been underestimated has been unknown. My estimates allow to put into perspective by just how much total healthcare costs have been underestimated to date. Other studies that quantify healthcare costs are limited to relatively narrow geographical areas and time periods and/or consider only a specific part of the population (Deryugina et al., 2019; Castro et al., 2017). The estimates from these studies are therefore even more difficult to compare to the results from this study.

7.3 Limitations

While the data on healthcare reimbursements include detailed information on the nature of the medical procedures and the associated costs of treatment, as well as some basic information on patient characteristics,

[16]France has a population of 67 million which is about 13% of the total EU population (513). Source: Eurostat

there is no information on the socioeconomic status of patients. It has been shown that education, income and socio-professional category influence health care consumption and health status. The inclusion of postcode fixed effects and the IV strategy should avoid bias that could arise from residential sorting by socioeconomic status and non-random exposure to air pollution. In addition, I analyse effect heterogeneity by observed patient characteristics (age, health status, enrolment in a government funded healthcare plan indicating low-income) and location characteristics as proxy for population characteristics. Nevertheless, this does not allow me to satisfactorily study the differences in effects according to socioeconomic status.

Another issue is the lack of clinical information, especially for certain risk factors such as smoking, weight, or body mass index.As long as daily variations in air pollution are not systematically correlated with individual smoking or drinking behaviour (controlling for day of the week FE), this should not lead to bias in my estimates. Adapting behaviours such as staying indoors and avoiding sports on high pollution days could, however, lead to an underestimate of the health costs associated with pollution exposure. Finally, I do not observe any healthcare consumption that would not have been subject to an insurance reimbursement. Neither self-medication nor the consumption of prescribed but not reimbursed drugs can be measured. This could again lead to an underestimation of the total effects. My estimates should therefore be considered a lower bound.

I assume that the postcode area of residence corresponds to the usual place of air pollution exposure. However, it is quite possible for individuals to be exposed to different concentrations of pollution than where they officially live, for example while they are at work or while travelling. To address this concern, I show in sensitivity analyses that the results hold when the analysis is conducted at the higher levels of spatial aggregation.

The study only considers the healthcare costs of short-term exposure to air pollution. While I find that these costs are sizeable enough to motivate further reduction in air pollution concentrations, the effects of chronic exposure to air pollution may be even more important in terms of overall public health relevance (Pope III et al., 2009) and merit further investigation.

A concern with interpreting my estimates as the causal effects of NO2, O3 and particulate matter is that I do not observe other air pollutants like carbon monoxide (CO) and sulfur dioxide (SO2) that are likely correlated with the pollutants I observe and have independent health effects. For future research, information on these pollutants should be included.

7.4 Policy recommendation

A review of EU rules is currently underway. One of the policy changes being discussed is a closer alignment of EU air quality standards with scientific knowledge, including the latest recommendations of the World Health Organization (WHO).[17] This planned revision is a step in the good direction. While the WHO limit values are not more stringent than the current EU framework for NO2, the revision would result in a reduction of the limit values for PM10 from an annual average of 40 $\mu g/m^3$ to 20 $\mu g/m^3$ for PM2.5 from 25 $\mu g/m^3$ to 10 $\mu g/m^3$. However, this study provides evidence for sizeable healthcare costs caused by levels of air pollution that are relatively low. The average PM10 concentration in the data used for this study is only $16.61 g/m^3$ and the PM2.5 concentration is $10.58 g/m^3$, which is below and close to the proposed new limit values, respectively. This suggests that an even stricter regulation than that of the WHO could avoid significant costs to healthcare systems. In addition to cost-benefit considerations, another argument for air pollution reduction is a concern for equity. The study provides evidence for significant heterogeneity of effects across patient characteristics and postcode areas, indicating that air pollution reduction policies have the potential to reduce health inequalities.

[17] `https://ec.europa.eu/environment/air/quality/revision_of_the_aaq_directives.htm`

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Appendix

Table A1: Summary of the main French Air Quality Standard values

Pollutants	Limit value	Quality objectives	Recommendation & info. threshold	Alert threshold
Nitrogen dioxide (NO2)	Annual mean: $40\mu g/m^3$. Hourly mean: $200\mu g/m^3$ not to be exceeded more than 18 per year.	Annual mean: $40\mu g/m^3$.	Hourly mean: $200\mu g/m^3$.	Hourly mean: $400\mu g/m^3$ exceeded on 3 consecutive hours. $200\mu g/m^3$ if the information level has already been reached the day before and the current day, and if a new exceedance is forecasted for the next day.
Sulphur dioxide (SO2)	Hourly mean: $125\mu g/m^3$ not to be exceeded more than 3 per year. Daily mean: $350\mu g/m^3$ not to be exceeded more than 24 per year.	Annual mean: $50\mu g/m^3$.	Hourly mean: $300\mu g/m^3$.	Hourly mean $500\mu g/m^3$ exceeded on 3 consecutive hours.
Particles with a diameter of $10\mu m$ or less (PM10)	Annual mean: $40\mu g/m^3$. Hourly mean: $50\mu g/m^3$ not to be exceeded more than 35 per year	Annual mean: $30\mu g/m^3$.	Daily mean: $50\mu g/m^3$.	Daily mean: $80\mu g/m^3$.
Carbon monoxide (CO)	Maximum daily on a 8-hour mean: $10000\mu g/m^3$.			
Ozone (O3)		Maximum daily eight-hour mean: $120\mu g/m^3$ per civil year.	Hourly mean: $180\mu g/m^3$.	Alert threshold, hourly mean: $240\mu g/m^3$ per hour. Alert threshold for emergency measures, hourly means: 1st threshold: $> 240\mu g/m^3$ during 3 consecutive hours. 2nd threshold: $> 300\mu g/m^3$ during 3 consecutive hours. 3rd threshold: $> 360\mu g/m^3$.
Particles with a diameter of $2.5\mu m$ or less (PM2.5)	Annual mean: $27\mu g/m^3$ decreasing every year by equal annual percentage to reach $25\mu g/m^3$ by 2015.	Annual mean: $10\mu g/m^3$.		

Source: Airparif, `https://www.airparif.asso.fr/en/reglementation/normes-francaises`
Limit value: a level set on the basis of scientific knowledge with the aim of avoiding, preventing or reducing harmful effects on human health and/or the environment as a whole, to be attained within a given period and not to be exceeded once attained. Target value: a level fixed with the aim of avoiding, preventing or reducing harmful effects on human health and/or the environment as a whole, to be attained where possible over a given period. Quality objectives: long-term level to achieve and maintain, except where this is not achievable through proportionate measures to ensure effective protection of human health and the environment as a whole. Information threshold: a level beyond which there is a risk to human health from brief exposure for particularly sensitive sections of the population and for which immediate and appropriate information is necessary. Alert threshold: a level beyond which there is a risk to human health from brief exposure for the population as a whole and at which immediate steps are to be taken by the Member States.

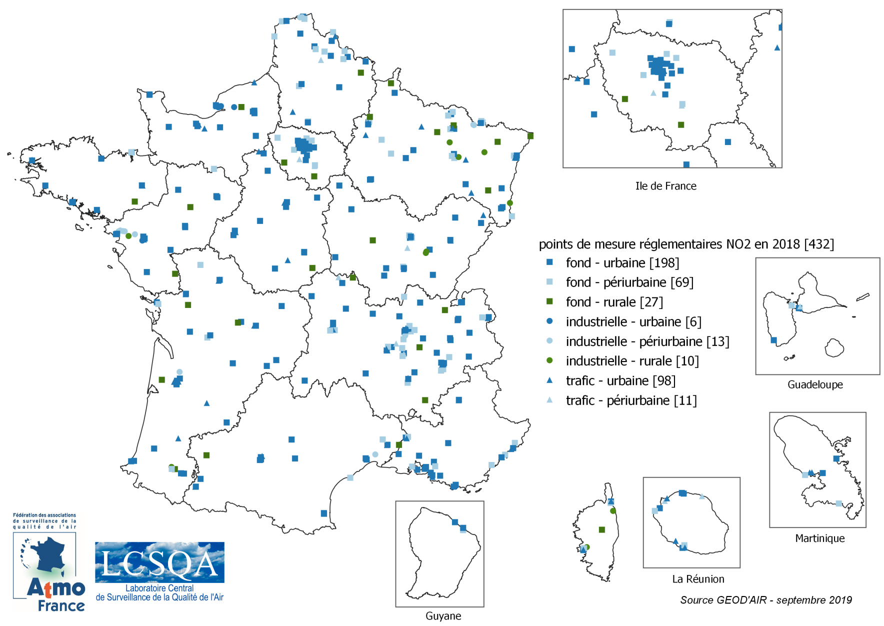

Figure A1: Map of the spatial distribution of NO2 measuring stations in France. *Source: GEOD'AIR available here.*

Table A2: Beaufort scale by wind speed and description of the land conditions.

Beaufort number	**Wind speed**	**Description**	**Land conditions**
0	0.5 m/s	Calm	Smoke rises vertically.
1	0.5 - 1.5 m/s	Light air	Direction shown by smoke drift but not by wind vanes.
2	1.6 - 3.3 m/s	Light breeze	Wind felt on face; leaves rustle; wind vane moved by wind.
3	3.4 - 5.5 m/s	Gentle breeze	Leaves and small twigs in constant motion; light flags extended.
4	5.5 - 7.9 m/s	Moderate breeze	Raises dust and loose paper; small branches moved.
5	8 - 10.7 m/s	Fresh breeze	Small trees in leaf begin to sway; crested wavelets form on inland waters.
6	10.8 - 13.8 m/s	Strong breeze	Large branches in motion; whistling heard in telegraph wires; umbrellas used with difficulty.
7	13.9 - 17.1 m/s	High wind, moderate gale	Whole trees in motion; inconvenience felt when walking against the wind.
8	17.2 - 20.7 m/s	Gale, fresh gale	Twigs break off trees; generally impedes progress.
9	20.8 - 24.4 m/s	Strong/severe gale	Slight structural damage (chimney pots and slates removed).
10	24. - 28.4 m/s	Storm, whole gale	Seldom experienced inland; trees uprooted; considerable structural damage.
11	28.5 - 32.6 m/s	Violent storm.	Very rarely experienced; accompanied by widespread damage.
12	$\geq$ 32.7 m/s	Hurricane force	Devastation.

Source: Royal Meteorological Society available here and MET office available here.

Table A3: Summary statistics - pooled postcode-day observations, entire sample

Variable	Mean	Std. Dev.	Min.	Max.	N
Health care spending					
Total spent	513.76	1415.4	0	351206.91	8835995
Family medicine	172.56	508.53	0	71455.65	8836033
Cardiology and vascular medicine	7.25	50.75	0	37072.16	8836120
Otorhinolaryngology	2.75	23.37	0	10190	8836122
Pulmonology	3.24	50.18	0	15664.6	8836126
Ophtalmology	11.73	64.19	0	6871.2	8836120
Neurology	2.8	46.1	0	10373.22	8836127
Trauma surgery	5.13	55.31	0	14687.84	8836114
Ambulance services	10.9	84.32	0	9434.66	8836112
Gynecology	6.15	41.46	0	6838.82	8836121
Gastroenterology and hepatology	4.61	111.49	0	26010.53	8836126
Rheumatology	4.07	48.72	0	11414.56	8836127
Stomatology	0.83	23.83	0	23800	8836126
Dental surgery	39.44	233.53	0	33874.4	8836111
Nephrology	1.63	24.86	0	11234.26	8836127
Plastic surgery	0.74	27.69	0	6321.91	8836128
Pollution measures					
NO2 emission (daily mean, g/m3)	13.8	8.44	0.09	138.44	8761974
PM 10 emission (daily mean, g/m3)	16.61	8.47	1.12	123.7	8761974
PM 2.5 emission (daily mean, g/m3)	10.58	7.44	0.32	104.97	8755985
O3 emission (daily mean, g/m3)	55.64	20.32	0	155.64	8761974
Meteorological conditions					
Temperature (daily mean, °C)	12.5	6.73	-19.4	34.6	8836128
Precipitation (daily sum, mm)	2.01	4.60	0	150.6	8836128
Wind speed (daily mean at 10m, m/s)	3.11	1.7	0	29.6	8836128
Strike measures					
Strike at postcode area level = 1	0	0.02	0	1	8836128
Strike at department level = 1	0.04	0.19	0	1	8836128
Strike at national level = 1	0.25	0.44	0	1	8836128
Strike at any geographical level = 1	0.29	0.45	0	1	8836128
Postcode characteristics					
Income	22096.28	4050.53	7910	52670	8790837
Unemployment rate	2.88	0.73	1	7.5	5744652
Gini index	0.32	0.05	0.21	0.63	5744652

Table A4: Summary statistics - pooled postcode-day observations, 10% most densely populated areas

Variable	Mean	Std. Dev.	Min.	Max.	N
Health care spending					
Total spent	2162.65	3373.44	0	351206.91	882437
Family medicine	716.32	1155.77	0	71455.65	882436
Cardiology and vascular medicine	32.11	117.7	0	37072.16	882437
Otorhinolaryngology	12.47	52.36	0	10190	882441
Pulmonology	13.73	113.19	0	15664.6	882444
Ophtalmo.	48.84	138.98	0	6871.2	882439
Neurology	11.29	86.31	0	6324.41	882444
Trauma surgery	19.04	111.7	0	14687.84	882442
Ambulance services	44.33	185.62	0	7159.73	882437
Gynecology	28.77	98.74	0	6838.82	882443
Gastroenterology and hepatology	20.77	256.75	0	25730.96	882442
Rheumatology	16.29	82.7	0	5842.46	882444
Stomatology	4	58.05	0	23800	882443
Dental surgery	170.33	522.71	0	33874.4	882438
Nephrology	8.27	54.38	0	9168.77	882443
Plastic surgery	3.46	62.49	0	6321.91	882444
Pollution measures					
NO2 emission (daily mean, g/m3)	19.47	11.83	1.13	138.44	877330
PM 10 emission (daily mean, g/m3)	18.23	9.52	1.75	123.7	877330
PM 2.5 emission (daily mean, g/m3)	11.61	8.23	0.79	104.97	876730
O3 emission (daily mean, g/m3)	51.24	21.95	0	149.24	877330
Meteorological conditions					
Temperature (daily mean, °C)	13.05	6.76	-10.5	34.6	882444
Precipitation (daily sum, mm)	1.87	4.46	0	132.3	882444
Wind speed (daily mean at 10m, m/s)	3.17	1.63	0	18.3	882444
Strike measures					
Strike at postcode area level = 1	0	0.07	0	1	882444
Strike at department level = 1	0.05	0.22	0	1	882444
Strike at national level = 1	0.25	0.44	0	1	882444
Strike at any geographical level = 1	0.3	0.46	0	1	882444
Postcode characteristics					
Income	22706.29	5613.86	7910	52670	880983
Unemployment rate	3.14	0.83	1	7.5	880983
Gini index	0.37	0.06	0.25	0.63	880983

Table A5: Summary statistics - pooled postcode-day observations, sample of 70 biggest cities

Variable	Mean	Std. Dev.	Min.	Max.	N
Health care spending					
Total spent	3550.97	5391.95	0	351206.91	241065
Family medicine	1152.02	1703.38	0	40544.62	241065
Cardiology and vascular medicine	55.57	157.88	0	8241.84	241058
Otorhinolaryngology	21.19	76.37	0	10190	241064
Pulmonology	21.68	133.34	0	7250.7	241065
Ophtalmology	78.04	192.76	0	5376.22	241062
Neurology	19.28	120	0	5481.27	241065
Trauma surgery	28.04	143.88	0	6950.02	241063
Ambulance services	70.61	246.44	0	6859.2	241063
Gynecology	51.14	145.08	0	6838.82	241065
Gastroenterology and hepatology	35.61	364.4	0	25730.96	241064
Rhumatology	27.57	108.32	0	5842.46	241065
Stomatology	6.83	84.44	0	23800	241064
Dental surgery	283.48	738.01	0	33874.4	241064
Nephrology	14.78	75.93	0	9168.77	241064
Plastic surgery.	6.18	79.91	0	5326.77	241065
Pollution measures					
NO2 emission (daily mean, g/m3)	22.87	12.86	1.28	138.44	237412
PM 10 emission (daily mean, g/m3)	19.28	9.89	1.87	123.7	237412
PM 2.5 emission (daily mean, g/m3)	12.18	8.39	0.79	104.97	237250
O3 emission (daily mean, g/m3)	50.21	22.57	0	142.47	237412
Meteorological conditions					
Temperature (daily mean, °C)	13.54	6.75	-8.1	34.6	241065
Precipitation (daily sum, mm)	1.8	4.47	0	132.3	241065
Wind speed (daily mean at 10m, m/s)	3.26	1.71	0	18.3	241065
Strike measures					
Strike at postcode area level = 1	0.02	0.13	0	1	241065
Strike at department level = 1	0.05	0.23	0	1	241065
Strike at national level = 1	0.25	0.44	0	1	241065
Strike at any geographical level = 1	0.31	0.46	0	1	241065
Postcode characteristics					
Income	22318.8	7189.22	7910	50570	241065
Unemployment rate	3.31	0.96	1	7.5	241065
Gini index	0.43	0.05	0.33	0.63	241065

Table A6: OLS and IV estimates of the effect of NO2 and O3 on healthcare spending

	Health spending 10% most populated areas	
	OLS	Wind IV
	(1)	(2)
NO2 mean	9.951***	23.98***
	(1.129)	(3.726)
Effect relative to mean (%)	0.5	1.1
O3 mean	2.607***	17.88***
	(0.282)	(2.487)
Effect relative to mean (%)	0.1	0.8
Dependent variable mean	2162.65	2162.65
Observations	837876	836730
First-stage F-stat		1356.1

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, department-month, month-year and postcode fixed effects.

Table A7: OLS and IV estimates of effect of one pollutant at a time on healthcare spending

Health spending - OLS regressions			
NO2 mean	4.677***		
	(0.326)		
O3 mean		-0.248***	
		(0.034)	
PM 10 mean			0.875***
			(0.080)
Observations	8495951	8495951	8495951
Health spending - Wind IV regressions			
NO2 mean	-0.794***		
	(0.190)		
O3 mean		0.436***	
		(0.090)	
PM 10 mean			-1.487***
			(0.244)
Observations	8484329	8484329	8484329
First-stage F-stat	8805.0	27595.0	6953.4

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month, year, and postcode fixed effects.

Table A8: OLS and IV estimates of the effects of NO2 and O3 on healthcare spending controlling for PM10 and effects of PM10 and O3 on healthcare spending contorolling for NO2

Panel A: *Effects of NO2 and O3 - PM10 as control*

	Health spending	
	OLS	Wind IV
	(1)	(2)
NO2 mean	6.542***	7.409***
	(0.455)	(0.941)
O3 mean	0.799***	3.735***
	(0.057)	(0.394)
PM 10 mean	-1.298***	-0.363
	(0.124)	(0.218)
Observations	8495951	8484329
First-stage F-stat		9716.0

Panel B: *Effects of PM10 and O3 - NO2 as control*

	Health spending	
	OLS	Wind IV
	(1)	(2)
PM 10 mean	-1.298***	1.226*
	(0.124)	(0.609)
O3 mean	0.799***	5.783***
	(0.057)	(0.396)
NO2 mean	6.542***	10.59***
	(0.455)	(0.680)
Observations	8495951	8484329
First-stage F-stat		12978.7

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

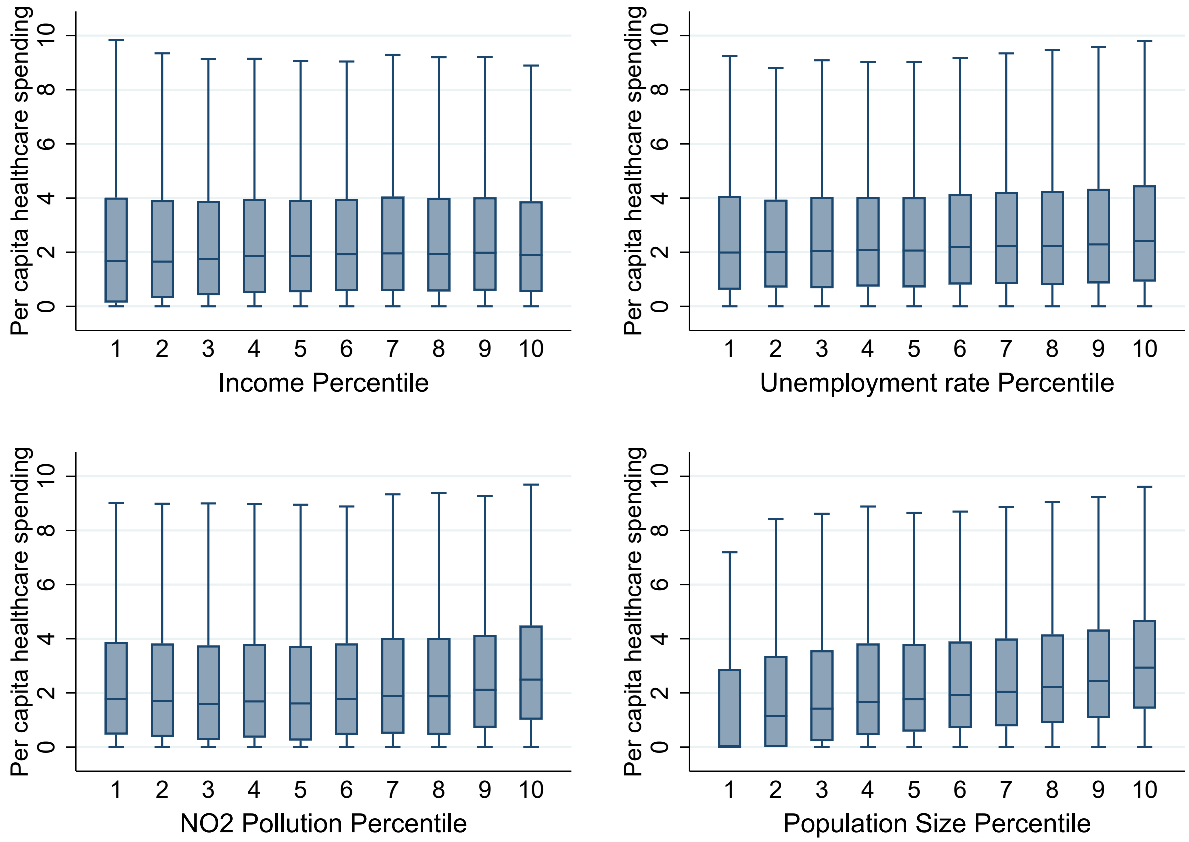

Figure A2: Box plots of per capita healthcare spending by postcode area average household income, unemployment rate, average NO2 pollution concentration and population size deciles. The lower and upper edges of the box show the 25th and 75th percentile, the bar in the box shows the median value. The length of the upper whisker is the largest value that is no greater than the third quartile plus 1.5 times the interquartile range. The lower whisker is defined analogously.

Table A9: Heterogeneous effects by postcode area characteristic, wind IV regressions

Panel A: *Heterogeneity by postcode average household income quartile*

	Per capita spent - 1st quartile	Per capita spent - 2nd quartile	Per capita spent - 3rd quartile	Per capita spent - 4th quartile
NO2 mean	0.0684	-0.00515	0.0431*	0.0436***
	(0.044)	(0.046)	(0.021)	(0.011)
O3 mean	0.0311	0.00132	0.0215*	0.0282***
	(0.018)	(0.018)	(0.010)	(0.006)
Observations	2077594	2033086	2022867	2022507
First-stage F-stat	1813.4	2262.2	2873.5	3821.0

Panel B: *Heterogeneity by postcode unemployment rate quartile*

	Per capita spent - 1st quartile	Per capita spent - 2nd quartile	Per capita spent - 3rd quartile	Per capita spent - 4th quartile
NO2 mean	0.0507***	0.0714***	0.0465*	0.0199
	(0.014)	(0.021)	(0.023)	(0.020)
O3 mean	0.0292***	0.0399***	0.0253*	0.0129
	(0.007)	(0.010)	(0.011)	(0.011)
Observations	1577512	1289367	1192350	1160988
First-stage F-stat	1830.2	1586.5	1407.9	1662.6

Panel C: *Heterogeneity by postcode average NO2 quartile*

	Per capita spent - 1st quartile	Per capita spent - 2nd quartile	Per capita spent - 3rd quartile	Per capita spent - 4th quartile
NO2 mean	0.0519	0.0764	0.0399	0.0205*
	(0.047)	(0.052)	(0.025)	(0.009)
O3 mean	0.0185	0.0330	0.0202	0.0157**
	(0.014)	(0.019)	(0.012)	(0.006)
Observations	2006811	2106407	2099479	1976914
First-stage F-stat	7570.5	8632.5	8733.3	7979.8

Panel D: *Heterogeneity by postcode population size quartile*

	Per capita spent - 1st quartile	Per capita spent - 2nd quartile	Per capita spent - 3rd quartile	Per capita spent - 4th quartile
NO2 mean	0.000189	0.0323	0.0486**	0.0426***
	(0.067)	(0.043)	(0.018)	(0.007)
O3 mean	0.000833	0.0190	0.0246**	0.0267***
	(0.028)	(0.018)	(0.008)	(0.004)
Observations	2008653	2075038	2094350	2011570
First-stage F-stat	2554.4	2318.3	2497.2	2458.7

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, month-by-department, month-by-year and postcode fixed effects.

Table A10: Impact of pollution on healthcare spending by age group

Panel A: *OLS regression, heterogeneity by age group*

	Age 0 to 10	Age 11 to 20	Age 21 to 30	Age 31 to 40	Age 41 to 50
NO2 mean	0.493***	0.578***	0.284***	0.685***	0.892***
	(0.035)	(0.048)	(0.032)	(0.060)	(0.064)
Effect relative to mean (%)	1.95	1.87	2.08	1.58	1.95
O3 mean	0.0489***	0.0793***	0.0322***	0.0434***	0.0938***
	(0.005)	(0.010)	(0.007)	(0.013)	(0.013)
Effect relative to mean (%)	0.2	0.3	0.2	0.1	0.2
Dependent variable mean	25.30	30.91	13.67	43.41	45.78
Observations	8737915	8737907	8737920	8737867	8737863

	51 to 60	Age 61 to 70	Age 71 to 80	Age 81 to 90	Over 90
NO2 mean	1.050***	0.992***	0.722***	0.595***	0.128***
	(0.087)	(0.071)	(0.065)	(0.057)	(0.021)
Effect relative to mean (%)	1.32	1.67	1.50	0.96	0.91
O3 mean	0.123***	0.115***	0.101***	0.0495***	0.0108*
	(0.018)	(0.012)	(0.013)	(0.012)	(0.005)
Effect relative to mean (%)	0.2	0.2	0.2	0.1	0.1
Dependent variable mean	79.28	59.55	48.05	61.76	14.02
Observations	8737818	8737825	8737897	8737905	8737918

Panel B: *IV regression, heterogeneity by age group*

	Age 0 to 10	Age 11 to 20	Age 21 to 30	Age 31 to 40	Age 41 to 50
NO2 mean	0.384	1.124***	-0.281	0.904*	0.522
	(0.207)	(0.280)	(0.184)	(0.397)	(0.319)
Effect relative to mean (%)	1.52	3.64	-2.06	2.08	1.14
O3 mean	0.184	0.532***	-0.160	0.420*	0.166
	(0.095)	(0.132)	(0.086)	(0.193)	(0.148)
Effect relative to mean (%)	0.7	1.7	-1.2	1.0	0.4
Dependent variable mean	25.30	30.91	13.67	43.41	45.78
Observations	8484417	8484412	8484422	8484372	8484367
First-stage F-stat	8805.3	8806.1	8805.5	8804.8	8804.9

	51 to 60	Age 61 to 70	Age 71 to 80	Age 81 to 90	Over 90
NO2 mean	0.526	2.153***	1.322***	0.997**	-0.0519
	(0.479)	(0.385)	(0.345)	(0.346)	(0.132)
Effect relative to mean (%)	0.66	3.62	2.75	1.61	-0.37
O3 mean	0.321	1.213***	0.765***	0.527**	-0.0138
	(0.226)	(0.183)	(0.166)	(0.163)	(0.062)
Effect relative to mean (%)	0.4	2.0	1.6	0.9	-0.1
Dependent variable mean	79.28	59.55	48.05	61.76	14.02
Observations	8484327	8484332	8484405	8484408	8484420
First-stage F-stat	8804.4	8805.0	8805.7	8805.6	8805.3

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include temperature and precipitation bins, day of the week, department by month, month by year and postcode fixed effects.

Table A11: OLS and IV estimates of effect of NO2 and O3 on healthcare spending

	No chronic disease		Chronic disease		No CMU		CMU	
	OLS	Wind IV	OLS	Wind IV	OLS	Wind IV	OLS	Wind IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NO2 mean	3.461***	1.612**	4.296***	7.815***	3.830***	4.097***	0.359***	0.189
	(0.239)	(0.604)	(0.332)	(0.919)	(0.328)	(1.126)	(0.045)	(0.219)
Effect wrt mean (%)	1.61	0.75	1.79	3.25	1.0	1.1	1.6	0.9
O3 mean	0.392***	0.928**	0.481***	3.799***	0.641***	1.830***	0.0538***	0.0966
	(0.033)	(0.290)	(0.059)	(0.435)	(0.053)	(0.548)	(0.010)	(0.104)
Effect wrt mean (%)	0.18	0.43	0.20	1.58	0.2	0.5	0.2	0.4
Dep. var. mean	215.09	215.09	240.23	240.23	372.35	372.35	22.23	22.23
Observations	8472603	8484259	8472731	8484387	8495959	8484337	8496034	8484412
First-stage F-stat		8805.3		8805.4		8804.9		8805.7

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A12: OLS estimates of effect of NO2 and O3 on healthcare spending by medical specialty

Panel A: *OLS estimates by medical specialty*

	Family medicine	O.R.L.	Ophthalmology	Stomatology	Dentistry
NO2 mean	1.751***	0.0543***	0.198***	0.0232***	0.891***
	(0.118)	(0.005)	(0.015)	(0.005)	(0.065)
O3 mean	0.145***	0.00537***	0.0177***	0.00309**	0.0818***
	(0.019)	(0.001)	(0.003)	(0.001)	(0.010)
Observations	8737859	8737946	8737944	8737950	8737935
	Cardio-vascular	Pneumology	Neurology	Gynecology	Ambulance
NO2 mean	0.140***	0.0339***	0.0393***	0.103***	0.141***
	(0.012)	(0.006)	(0.006)	(0.010)	(0.016)
O3 mean	0.0113***	0.00261	0.00372*	0.00726***	0.0267***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Observations	8737944	8737950	8737951	8737945	8737936
	Gastrohepatology	Rhumatology	Nephrology	Trauma surgery	Plastic surgery
NO2 mean	0.0502***	0.0136***	0.0824***	0.0824***	0.0255***
	(0.016)	(0.016)	(0.006)	(0.009)	(0.005)
O3 mean	0.00636	0.00301	0.00247*	0.00792***	0.00362**
	(0.005)	(0.002)	(0.001)	(0.002)	(0.001)
Observations	8737950	8737951	8737951	8737939	8737952

Panel B: *OLS estimates by medical specialty - weekday FE interacted with postcode FE*

	Family medicine	O.R.L.	Ophthalmology	Stomatology	Dentistry
NO2 mean	2.552***	0.0551***	0.201***	0.0283	1.111***
	(0.213)	(0.011)	(0.035)	(0.018)	(0.137)
O3 mean	0.419***	0.0117	0.0179	0.00914	0.171**
	(0.115)	(0.006)	(0.015)	(0.006)	(0.054)
Observations	835579	835585	835582	835586	835581
	Cardio-vascular	Pneumology	Neurology	Gynecology	Ambulance
NO2 mean	0.150***	0.0202	0.0899***	0.126***	0.312***
	(0.033)	(0.019)	(0.019)	(0.026)	(0.049)
O3 mean	0.0358**	0.00587	0.00947	0.0153	0.110***
	(0.012)	(0.012)	(0.009)	(0.012)	(0.022)
Observations	835580	835587	835587	835586	835580
	Gastrohepatology	Rhumatology	Nephrology	Trauma surgery	Plastic surgery
NO2 mean	0.0349	0.0488*	0.00386	0.0842**	0.0532*
	(0.068)	(0.020)	(0.014)	(0.028)	(0.022)
O3 mean	0.0274	-0.00210	0.0173*	0.00169	0.0140
	(0.030)	(0.010)	(0.007)	(0.014)	(0.008)
Observations	835585	835587	835586	835585	835587

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week by postcode, month, year and postcode fixed effects.

Table A13: Wind IV estimates of effect of NO2 and O3 on healthcare spending by medical specialty - entire sample

	Family medicine	O.R.L.	Ophthalmology	Stomatology	Dentistry
NO2 mean	1.777***	-0.0338	0.0187	0.00894	0.0615
	(0.466)	(0.028)	(0.077)	(0.031)	(0.273)
O3 mean	0.959***	-0.0145	0.0142	0.00501	0.0182
	(0.217)	(0.013)	(0.036)	(0.014)	(0.127)
Observations	8484366	8484449	8484446	8484452	8484437
First-stage F-stat	8805.1	8805.3	8805.4	8805.3	8805.3

	Cardio-vascular	Pneumology	Neurology	Gynecology	Ambulance
NO2 mean	-0.0379	-0.0597	0.00361	0.0371	0.838***
	(0.056)	(0.072)	(0.059)	(0.048)	(0.111)
O3 mean	-0.0149	-0.0286	0.00362	0.0198	0.413***
	(0.027)	(0.033)	(0.027)	(0.023)	(0.052)
Observations	8484446	8484452	8484453	8484448	8484439
First-stage F-stat	8805.2	8805.3	8805.3	8805.4	8805.3

	Gastrohepatology	Rhumatology	Nephrology	Trauma surgery	Plastic surgery
NO2 mean	0.250	0.0484	0.0293	0.0551	-0.00423
	(0.178)	(0.066)	(0.031)	(0.071)	(0.036)
O3 mean	0.110	0.0234	0.0141	0.0295	-0.00533
	(0.084)	(0.030)	(0.014)	(0.034)	(0.017)
Observations	8484452	8484453	8484453	8484441	8484454
First-stage F-stat	8805.3	8805.3	8805.3	8805.3	8805.3

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.

Table A14: OLS and IV estimates of effect of NO2 and O3 on healthcare spending - robustness to different fixed effect structures

	Health spending							
	simpler FE		simpler FE no weather contr		simpler FE no day of week FE		Pollution and weather lags	
	OLS (1)	Wind IV (2)	OLS (3)	Wind IV (4)	OLS (5)	Wind IV (6)	OLS (7)	Wind IV (8)
NO2 mean	5.784***	7.566***	4.185***	11.92***	17.35***	24.82***	7.230***	29.81***
	(0.380)	(1.240)	(0.286)	(2.058)	(0.586)	(1.296)	(0.498)	(2.745)
O3 mean	0.894***	3.942***	0.494***	7.710***	1.800***	12.25***	0.866***	15.76***
	(0.059)	(0.591)	(0.038)	(1.246)	(0.073)	(0.631)	(0.072)	(1.464)
Observations	8495951	8484329	8761843	8484329	8495951	8484329	8472673	8472673
Fs F-stat		8805.0		9163.6		8259.5		7364.7

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month, year, and postcode fixed effects.

Table A15: IV estimates of effect of NO2 and O3 on healthcare spending - different wind IV specifications

	Health spending[a] (1)	Health spending[b] (2)	Health spending[c] (3)	Health spending[d] (4)
NO2 mean	5.680***	7.462***	6.632***	7.359***
	(1.348)	(1.004)	(0.831)	(0.722)
O3 mean	3.026***	3.892***	3.534***	3.869***
	(0.634)	(0.465)	(0.387)	(0.336)
Observations	8490140	8478518	8490140	8484329
First-stage F-stat	792045.1	400783.7	1615143.0	541359.2

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

[a] - NO2 and O3 pollution are instrumented by two dummies equal to 1 when wind is below average on day t, and t-1, respectively, and 0 otherwise.

[b] - NO2 and O3 pollution are instrumented by four dummies equal to 1 when wind is below average on day t, t-1, t-2, and t-3 respectively, and 0 otherwise.

[c] - NO2 and O3 pollution are instrumented by absolute wind speed on day t, and t-1.

[d] - NO2 and O3 pollution are instrumented by absolute wind speed on day t, t-1, and t-2.

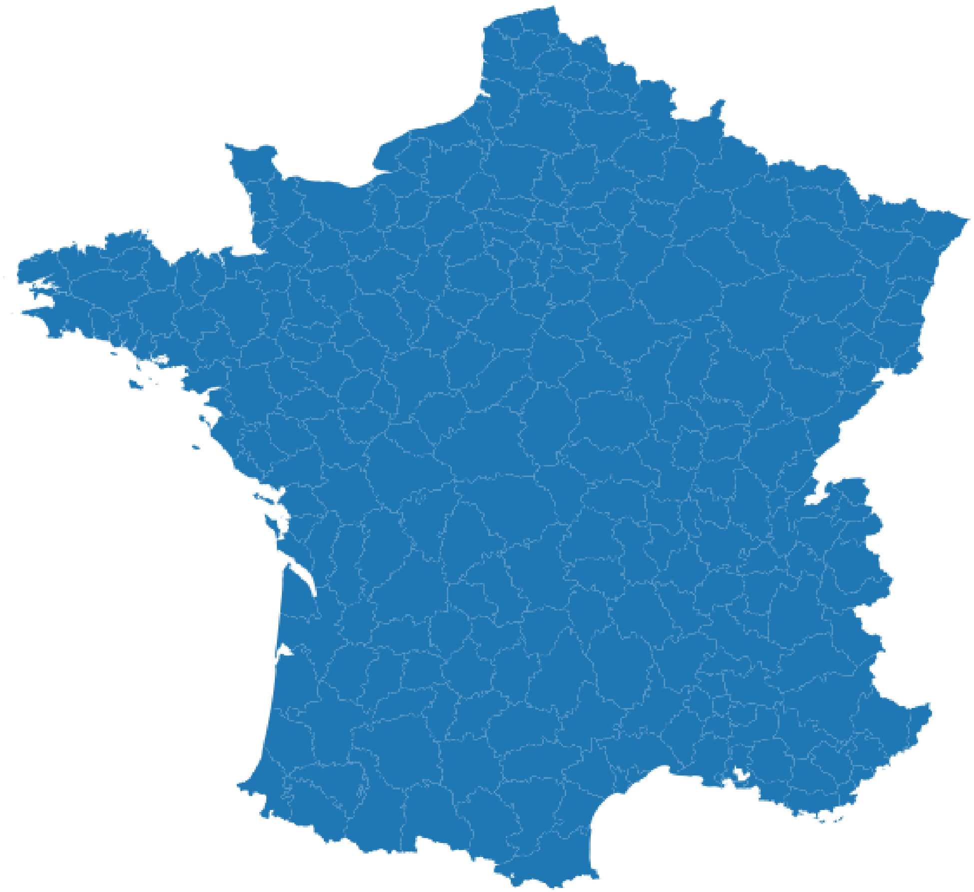

Figure A3: Division of France into 306 employment zones.

Table A16: OLS and IV estimates of the effect of NO2 and O3 on healthcare expenditure - analyses at the employment zone level

	Health spending	
	OLS	Wind IV
	(1)	(2)
NO2 mean	2.521***	6.469***
	(0.099)	(1.631)
O3 mean	0.397***	2.995***
	(0.035)	(0.699)
Observations	404268	403716
First-stage F-stat		26291.4

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the employment zone level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A17: OLS and IV estimates of the effect of NO2 and O3 on sick leave payments and mortality

	Sick leave spending		Number of deaths	
	OLS	Wind IV	OLS	Wind IV
	(1)	(2)	(3)	(4)
NO2 mean	0.00835*	0.147*	0.0000130**	-0.0000819
	(0.004)	(0.065)	(0.000)	(0.000)
O3 mean	0.00530**	0.0761*	0.00000327*	-0.0000419
	(0.002)	(0.031)	(0.000)	(0.000)
Observations	8496076	8484454	8496076	8484454
First-stage F-stat		8805.3		8805.3

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A18: Wind direction IV and thermal inversion IV estimates of the effect of NO2 and O3 on healthcare spending

	Tot. spending 70 biggest cities[a]	Tot. spending entire France		
	Wind dir. IV	Therm. inv. IV[b]	Therm. inv. IV[c]	Therm. inv. IV[d]
NO2 mean	165.9***	0.662	9.424***	15.26
	(2.587)	(0.579)	(0.757)	(9.096)
O3 mean	92.97***	-0.0556	4.004***	6.684
	(3.183)	(0.115)	(0.443)	(4.169)
Observations	215497	8490140	8490140	8490140
First-stage F-stat	389.4	5444.7	6361.0	7724.5

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis.
[a] Regression run on the sample of the 70 biggest cities due to computing power issues. This model includes a vector of temperature and precipitation bins and day of the week, month, year, and postcode fixed effects.
[b] Regression instruments for NO2 pollution only while O3 pollution is added as control.
[c] Regression instruments for O3 pollution only while NO2 pollution is added as control.
[d] Regression instruments simultaneously for NO2 and O3 pollution using the indicator variable for thermal inversion and its lag to have a suitable amount of instruments.
Models using thermal inversion as instrument include a vector of temperature and precipitation bins and day of the week, department by month, month by year, and postcode fixed effects.

Table A19: First stage regressions of the strike IV on pollution concentrations, corresponding to the IV regressions shown in Table A20

	NO2 mean	O3 mean	PM 10 mean
Strike day 1	0.0802***	-0.200***	-0.288***
	(0.007)	(0.016)	(0.008)
Strike day 2	1.087***	-1.107***	0.248***
	(0.013)	(0.026)	(0.019)
Strike day 3	0.592***	-1.952***	-0.358***
	(0.015)	(0.030)	(0.018)
Observations	6539974	6539974	6539974

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include a vector of temperature and precipitation bins and day of the week, month by department, month by year, and postcode fixed effects.

Table A20: Strike IV estimates of effect of NO2 and O3 on healthcare spending by medical specialty

	Family medicine	O.R.L.	Ophthalmology	Stomatology	Dentistry
NO2 mean	5.883***	0.108*	0.466***	0.0820	3.642***
	(0.702)	(0.044)	(0.118)	(0.045)	(0.496)
O3 mean	4.119***	0.146**	0.798***	0.0141	2.412***
	(0.773)	(0.048)	(0.132)	(0.052)	(0.509)
Observations	6539891	6539971	6539968	6539973	6539966
First-stage F-stat	3765.9	3765.8	3765.6	3765.8	3765.9
	Cardio-vascular	Pneumology	Neurology	Gynecology	Ambulance
NO2 mean	0.283**	0.0453	0.111	0.351***	0.338*
	(0.096)	(0.090)	(0.082)	(0.087)	(0.161)
O3 mean	0.382***	0.314***	0.368***	0.317***	0.339*
	(0.106)	(0.095)	(0.111)	(0.076)	(0.157)
Observations	6539973	6539972	6539974	6539970	6539963
First-stage F-stat	3765.8	3765.8	3765.8	3766.9	3765.8
	Gastrohepatology	Rhumatology	Nephrology	Trauma surgery	Plastic surgery
NO2 mean	0.429	0.0984	0.0169	0.412***	0.179*
	(0.232)	(0.094)	(0.043)	(0.117)	(0.070)
O3 mean	0.259	0.253**	0.0143	0.380**	-0.0108
	(0.295)	(0.096)	(0.049)	(0.122)	(0.054)
Observations	6539972	6539973	6539973	6539962	6539974
First-stage F-stat	3765.8	3765.8	3765.8	3765.6	3765.8

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Robust standard errors clustered at the postcode level in parenthesis. All models include day of the week, day of the month, month and postcode fixed effects.