WORKING PAPER

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

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Abstract

I estimate the effects of air pollution on health care use and costs using administrative data on health care reimbursements in France and reanalysis data on concentrations of nitrogen dioxide (NO2), ozone (O3) and fine particles pollution (PM 10 and PM 2.5). To establish a causal relationship, I exploit daily variation in air pollution intensity induced by variations in wind speed, wind direction and periods of strikes in the public transport sector. I estimate that each 1 $\mu g/m^3$ increases in daily NO2 (7.2% of the average) results in an increase of €7.57 in daily health expenditure per postcode area, while each 1 $\mu g/m^3$ increase in daily O3 (1.8% of the average) results in an increase of €3.94, which corresponds respectively to a 1.5% and 0.8% increase in average daily expenditure. Summing across postcode areas and scaling the effects appropriately, this translates into an increase in health expenditure of €6.8 million per day or €2.5 billion per year. These costs are the result of exposure to pollution levels that are mostly well below the current regulatory levels. In addition, the estimates reflect only the costs of short-term exposure to air pollution while the potentially even larger effects of long-term exposure are not considered. These high costs from short-term exposure alone suggest that there are considerable benefits to reducing air pollution even further below current limit values. Finally, I find significant heterogeneity of effects across location and patient characteristics, indicating that air pollution reduction policies have the potential to reduce health inequalities.

JEL: I12, J14, Q51, Q53

1 Introduction

Exposure to air pollution has well-documented adverse effects on human health such as 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. Yet, 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 critical in determining 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 estimate the causal effects of air pollution on health care use and costs in France, where pollution levels are on average below the current limit values.

Estimating the causal effect of air pollution on health care costs is difficult due to problems of endogeneity and a general lack of adequate data. People sort spatially according to preferences and characteristics which may be correlated both with their health status and their level of 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 levels of pollution are on average higher. Failure to consider such non-random exposure results in biased estimates of the effects of pollution on health and health care costs. Without information on incomes or preferences, many researchers have relied on quasi-experimental designs that use a plausible 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 time 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. This is a rather extreme event that is less likely to occur following exposure to moderate levels of pollution.

In this study, I investigate the causal short-term effects of exposure to nitrogen dioxide (NO2), ground-level ozone (O3) and fine particles pollution (PM 10 and PM 2.5) on health and health care costs in a representative sample of the French population. I combine unique administrative data on daily health care reimbursements from 2015 to 2018 for all types of health care with exceptionally fine-grained reanalysis data on daily pollution levels and meteorological conditions, and hand-collected data on public transport strikes. I adopt an instrumental variable (IV) approach where I use as IVs the daily variation in the intensity of air pollution at the postcode area level induced by variation in wind speed, wind direction and periods of strike in the public transport sector. The identifying assumption is that variation in pollution due to changes in wind speed, wind direction or public transport strikes is unrelated to changes in health care use or costs except through the influence on air pollution. This should be the case after flexibly controlling for various time and location fixed effects and several additional covariates such as climatic conditions. Wind direction and common levels of wind speed are unlikely to have a direct effect on health care use other than through the effect on air pollution and I do not find evidence for increased health care use on days of high wind speed. Concerning public sector strikes, the exclusion restriction should hold at least for some selected medical specialties such as cardio-vascular and respiratory care which I can 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, or specialties that are likely to be unresponsive, such as plastic surgery, and serve as placebo.

I find that each 1 g/m3 increase in daily NO2 (7.2% of the mean) cause an increase of €7.57 in aggregate health care spending whereas each each 1 g/m3 in daily O3 (1.8% of the mean) causes an increase of €3.94 which corresponds to an increase of 1.5% and 0.8% relative to the average daily spending. Using strikes as instrument rather than wind speed yields even larger estimates. These estimates reflect the costs of acute (short-term) exposure to air pollution, without considering the potentially greater 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, this translates into an increase in health expenditure 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). According to my estimates, 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. The benefits from a reduction in short-term health care costs due to the decreased NO2 pollution alone (disregarding the changes in other pollutant levels and effects on mortality or productivity, natural systems, etc.) sets off 40% of the total costs of compliance with the NEC directive.

I further find significant heterogeneity in effects across patient characteristics and postcode areas. The increase in health expenditure for an increase in daily NO2 or O3 is 4-6 times higher in the most unequal postcode areas (postcode Gini Index is in the highest quintile) compared to the most equal postcode areas (postcodes Gini Index is in the first quintile). The effects are 1.4 to 2.1 times stronger in the postcode area with the highest quintile of unemployment rate compared to the postcode area with the lowest quintile of unemployment rate. Yet, the effect relative to the mean is similar between the first and last quintiles because of the higher average health care spending in the postcode areas with the highest Gini Index or highest unemployment rates compared to the areas with the lowest Gini Index or unemployment rates. 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,

[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`

but the effect relative to average age group expenditures is more similar across age groups. This could be because most studies find stronger effects in the young and elderly with respect to mortality, which is a rather extreme event likely to affect only the most vulnerable, whereas I am looking at health care costs that include the costs of treating milder health effects that appear to manifest across all age groups.

This study contributes to the recent quasi-experimental literature on the health effects of air pollution. The idea of exploiting public transport sector strikes or meteorological conditions to estimate the causal effects or air pollution on health is not new. In a working paper, Giaccherini et al. (2019) exploit public transportation strikes as exogenous shocks to pollution. However, the scope of this work is much smaller than the present study as it focuses on the effects of particulate pollution on hospital admissions and costs in 111 Italian municipalities. Similar studies that also use data on pollution and public sector strikes are Godzinski and Suarez Castillo (2019) investigate the impact of public transport strikes on hospital admissions for influenza, gastroenteritis and respiratory diseases in the 10 major cities in France and Bauernschuster et al. (2017) investigate the impact of strikes on hospital admissions for respiratory disease in a selection of German cities. Again, the scope these studies is much smaller. In addition, the objective of these studies differs as the authors study the impact of strikes on health rather than the impact of strike-induced pollution. An example of a recent paper using meteorological conditions is Deryugina et al. (2019) which estimates the causal effects of acute fine particulate matter exposure on mortality, health care 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). Much of this work considers avoided mortality costs. This is a rather extreme event that is less likely to occur following exposure to moderate levels of pollution. Total health care costs related to the treatment of conditions that are caused or aggravated by air pollution are generally not quantified directly as detailed information on total health care expenditure is rarely available.

I estimate health care expenditure more accurately and comprehensively than has been done before. To the best of my knowledge, this is the first quasi-experimental study to comprehensively quantify the health care costs caused by exposure to moderate levels of air pollution in a nationwide representative sample. I also explore treatment effect heterogeneity both by location and patient characteristics in greater depth than 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, unemployment rates, and income inequality. Observed patient characteristics include age, sex and chronic health condition.

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 are included in these models. I am not aware of any study that comprehensively quantifies health care costs in France. 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) considered only asthma and cancer as sufficient health and economic data were not available for all air pollution-related diseases. 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 which is extremely small compared to my estimate of €2.5 billion for a 1 $\mu g/m^3$ change in air pollution concentrations. Another study carried out by the General Commission for Sustainable Development in 2015 sought to assess as comprehensively as possible the cost of air pollution to the French health care system (Rafenberg, 2015). However, the study only covers a selection of disease categories (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 again smaller than my estimate of the effects of a 1 $\mu g/m^3$ change in air pollution levels. In a study relying similarly on dose response estimates but using UK data, 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, 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 health care 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 health care costs have been underestimated to date.

This study presents evidence of non-negligible health care costs caused by acute (short-term) exposure to air pollution at levels that are on average below current 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).[2] 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 health care 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 health care 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, strikes in the public transport sector and air pollution levels. Section 3 describes my data, section 4 describes the empirical strategy, section 5 presents results, and Section 6 discusses the findings and concludes.

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

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

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 3 shows daily mean and daily maximum hourly pollution levels 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 Public transport strikes, wind speed and their effects on air pollution levels

Strikes in the public transport sector are not uncommon in France. For example, there were an average of 21 separate national strikes per year at SNCF, the French national railway company between 2015 and 2019.[3] Since 2007, public transport service employees are obliged to indicate forty-eight hours in advance that they intend to go on strike to enable local authorities to reorganise the most important services, substituting non-strikers for strikers. However, this law did not establish a real minimum service obligation in public transport as it does not allow the requisitioning of striking employees. When a large share of the workforce goes on strike, the transport operator cannot redeploy non-strikers throughout the network for lack of human resources.[4] 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.

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

[3] Calculated using data from `https://ressources.data.sncf.com`.

[4] Law n2007-1224 of 21 August 2007 ”on social dialogue and the continuity of public service in regular land passenger transport” (JO, 22 August 2007, p. 13 956) voted on 2 August 2007 under the Fillon II government. See `https://www.legifrance.gouv.fr/affichTexte.do?cidTexte=JORFTEXT000000428994&categorieLien=id`.

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. Concerning particulate matter and ozone, the total contribution of road transport is more difficult to quantify. While particulate matter is also directly emitted from cars, it is mostly created by secondary formation from precursor emissions such as NOx. 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. 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. This degradation occurs more often in cities as there are higher levels of NO due to traffic which react with ozone to form NO2. It also explains why short-term decreases in traffic (decrease in the NO concentration) can have adverse effect on ozone pollution (IRCEL, 2020).

In my data, NO2 and ozone are generally inversely related which is consistent with the pollution dynamics described above. On days of strike, I find increases in daily NO2 levels whereas ozone levels decrease. The relation between public transport strikes and particulate matter pollution is inconclusive. I see an increase in particle pollution on the first day of the strike, but a decrease on the second day. The lack of a clear increase in PM on strike days is not surprising considering that PM is mostly created by secondary formation from precursor emissions, which means that the link between PM and road traffic emissions is mostly indirect. See Table 2 and Table A6 in the appendix for the coefficients from regressions of the pollutants on the strike instruments (first stage regression). Figure 1 graphically illustrates the relationship between public transport strikes and NO2 pollution by showing maps of NO2 pollution at postcode level one day before, one day during and two days after a national public transport strike. Levels of NO2 visibly increase on the day of the national public transport strike relative to the days before and after.

It is generally well established that wind speed strongly affects the degree of accumulation of air pollutants near emission sources such as traffic in urban environments. Wind carries 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; Pearce et al., 2011; Grundström et al., 2015; Cichowicz et al., 2020). This is confirmed in my data. I find that pollution is higher on days of lower wind speed. See Tables 2 and A6 in the appendix 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. Figure 2 graphically illustrates the relationship between wind speed and NO2 pollution by showing maps of

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

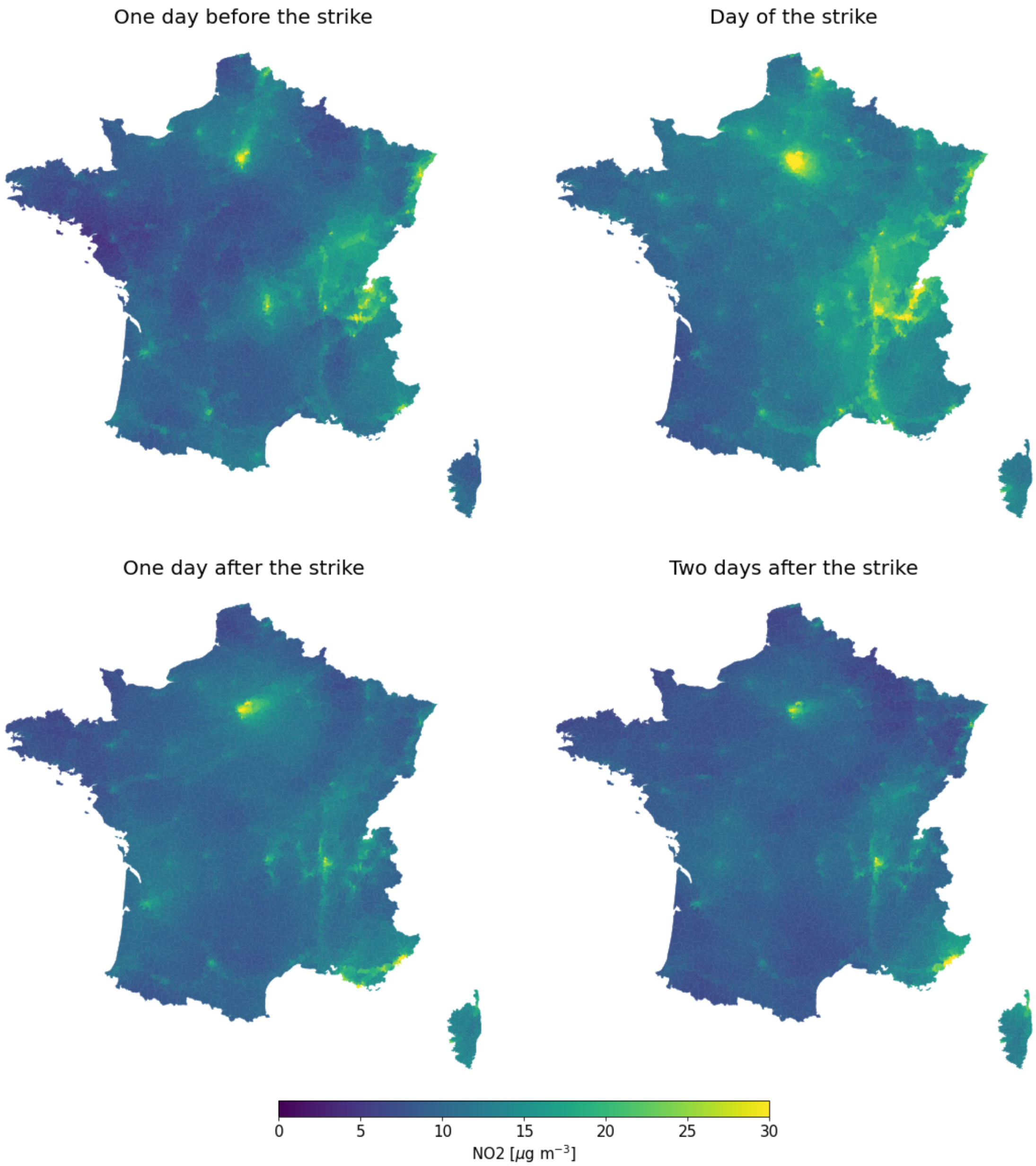

Figure 1: Level of NO2 pollution for four consecutive days, one day before a national strike, the day of the strike and one and two days after the strike.

NO2 pollution and wind speed at postcode level for two days of generally low wind speed and two days of generally high wind speed. NO2 concentration is visibly higher when wind speed is low.

3 Data

I combine administrative data on health care 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 Health care use and costs

I use administrative data on health care reimbursements from the French National System of Health Data (SNDS for *Systme National des Donnes de Sant*) covering the period 2015 to 2018. The French health care system is based on universal coverage by one of several health care 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 health care, 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 specialties. 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 Gnraliste de Bnficiaires*). 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 health care 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 health care use and cost by the patient's postcode area of residence. For heterogeneity analyses, I additionally group by patient characteristics.

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 in-

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

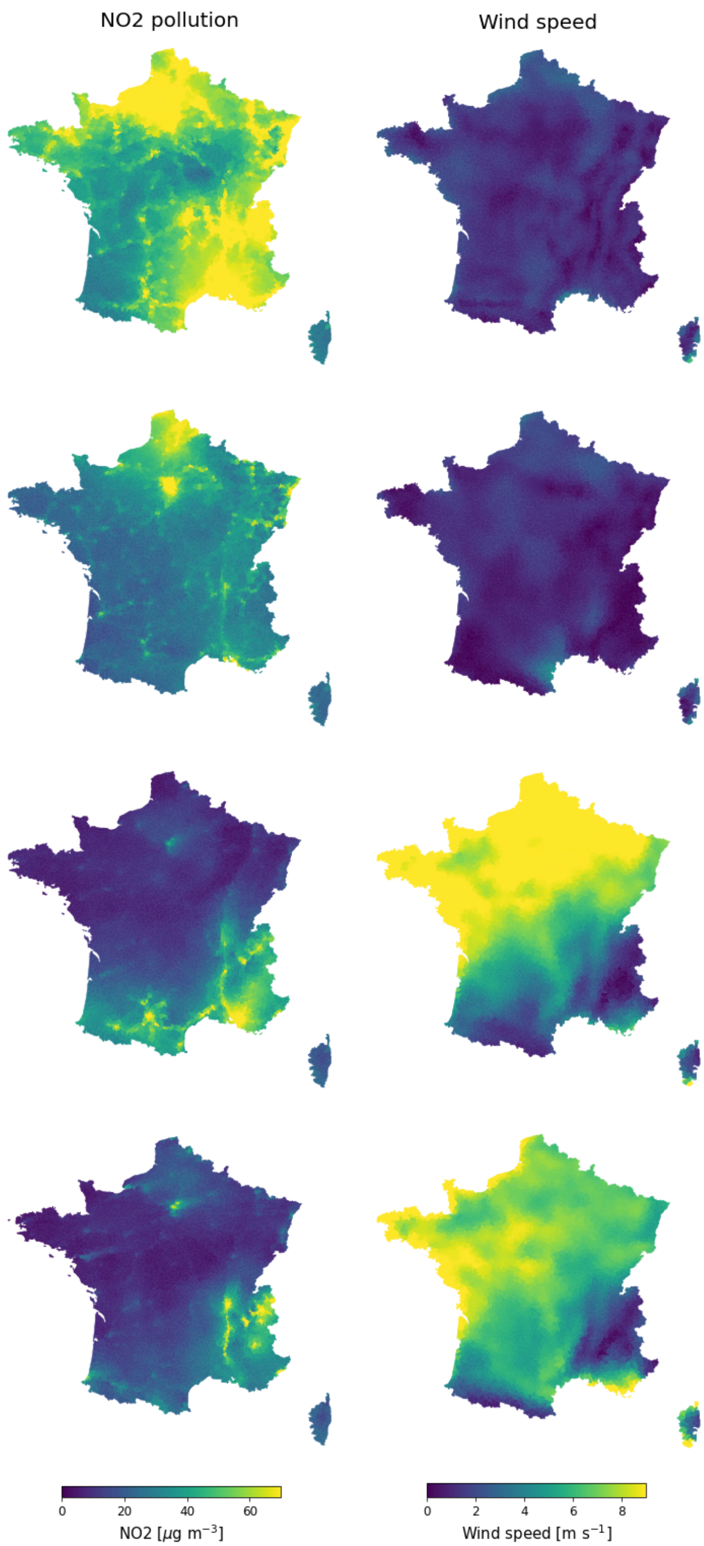

Figure 2: Level of NO2 and wind speed for two days of low wind speed (rows 1 and 2) and two days of high wind speed (rows 3 and 4).

cluding 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 mdicale universelle complmentaire*), 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-single-levels?tab=overview`. These data are in the form of raster files with a spatial resolution of 9x9 km2. 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 Public transport strikes and other additional data

Information on the dates and locations of public transport strikes are collected manually 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 exploit data on the percentage of agents at the French National Railway Company (SNCF for *"Socit nationale des chemins de fer franais"*) 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/`.

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 tudes conomiques in French). This database generally includes income distribution indicators reported by households, for all households and by household category and is publicly availably 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`.

Summary statistics

Table A2 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 A3 and A4 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 3 which displays the distribution of daily maximum hourly and daily mean pollutant concentration together with the corresponding limit value. Figure 4 shows how average health care expenditure and pollutants vary by day of the week and month, showing significant cyclical changes over the week and seasons.

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 health care use and costs. Exploiting daily variation in the intensity of air pollution at the postcode area level, I estimate the following model:

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

where H_{dpc} denotes health care use or cost on day d in postcode area p and for medical specialty c. I regress this on the pollution level P_{dpx} of pollutant x on day d in postcode area p. 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 health care use. I also flexibly control for seasonality in air pollution and health care 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

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

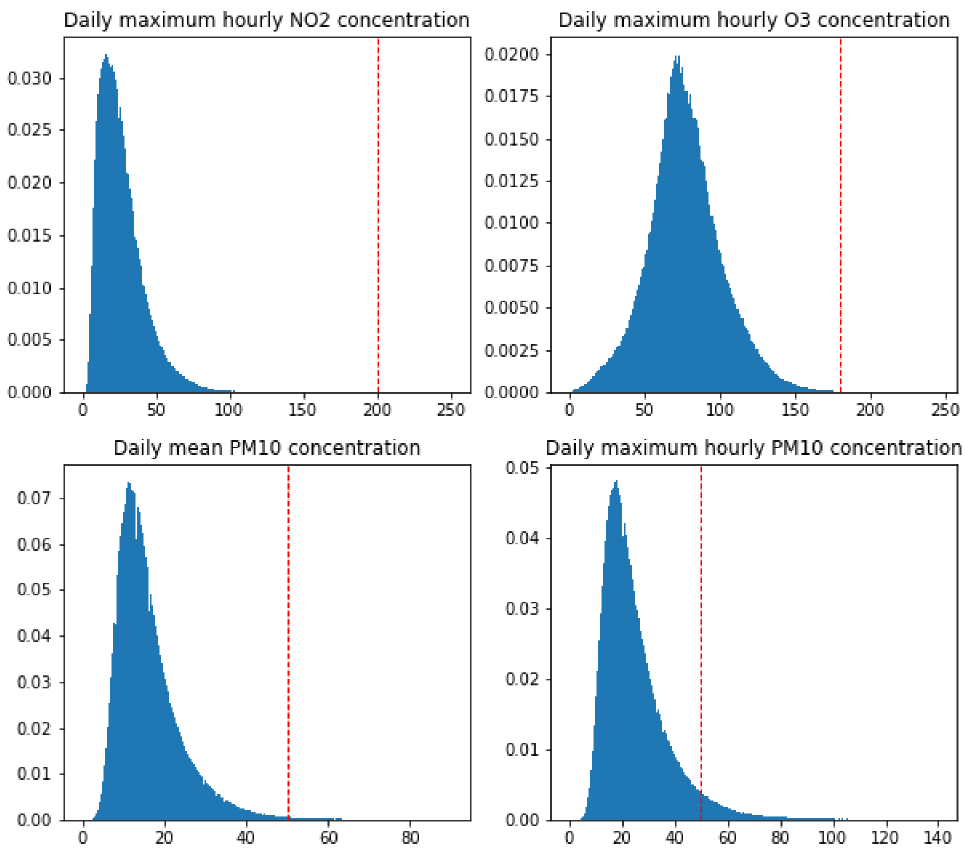

Figure 3: Level of pollutants relative to the limit values presented in Table A1.

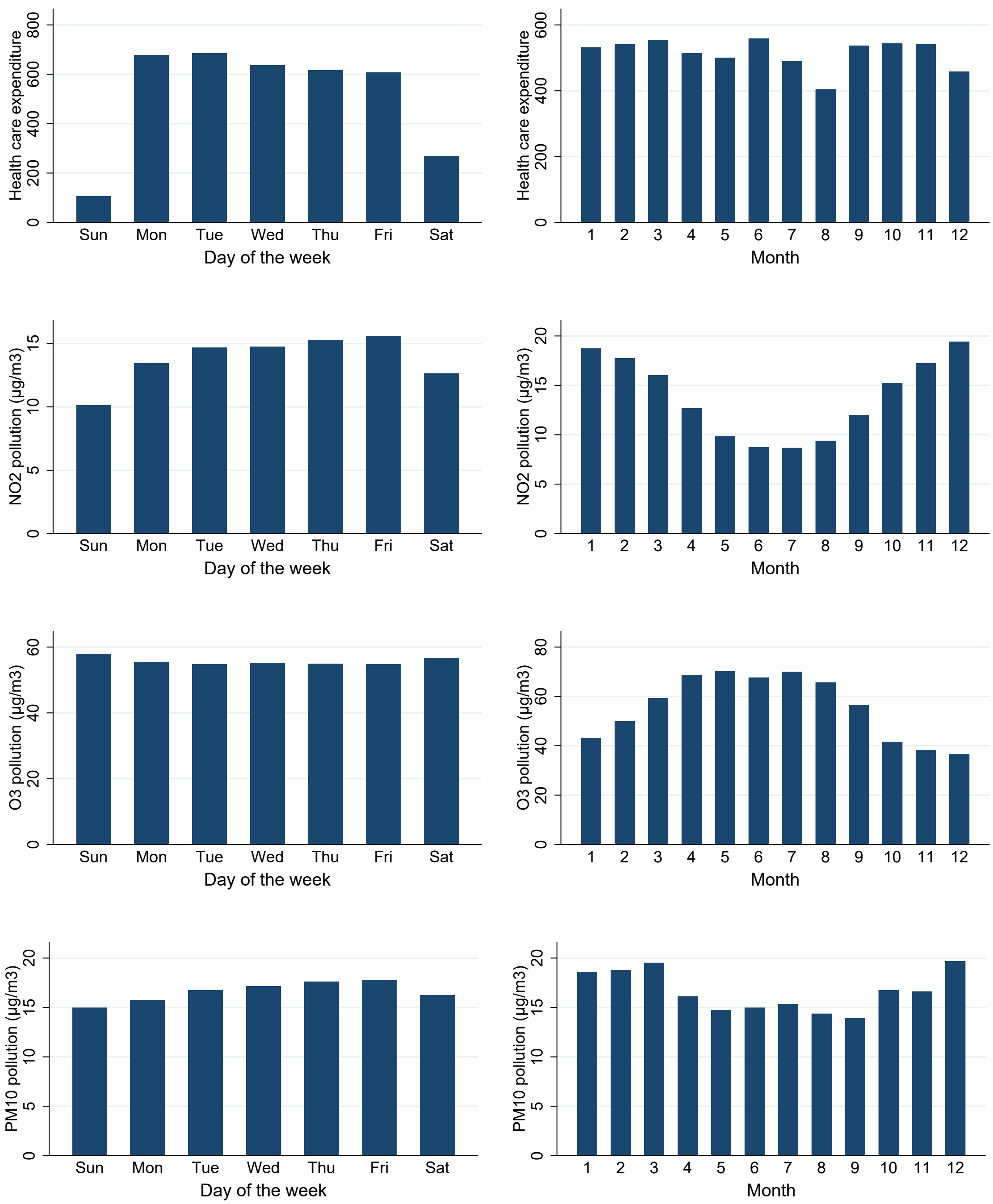

Figure 4: Mean of health care expenditure and pollutants by day of the week and month.

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. Standard errors are clustered at the postcode level. In some specifications, I include up to three lags of the air pollutants and weather variables to consider the possibility that pollution build-up over the past days may impact health outcomes.

4.2 Wind speed and public transport sector strikes as instruments for air pollution

Both air pollution levels and health care use change cyclically throughout the week (see Figure 4) and appear to be correlated with economic activity. A possible cause for concern is that the fixed effect structure in equation (1) does not correctly purge these effects. To address this potential issue, I estimate instrumental variable (IV) models in which I use wind speed as instrument for air pollution levels. Wind speed is plausibly exogenous to economic activity, which means that the IV approach should allow me to estimate the effects of air pollution on health care use and costs without accidentally capturing correlations due to economic activity.

It is possible that individuals chose their place of residence not only considering average pollution levels but their decision may also be influenced by the range of variation in pollution levels. For example, individuals may want to avoid proximity to pollution sources that produce extreme levels of pollution even if such levels occur less frequently and do not translate into a higher average level of pollution. If the range of variation in pollution is a function of unobserved individual characteristics and if the health effects of high deviations from average pollution level differ compared to relatively smaller deviations, then my estimates could still be biased despite controlling for all location and spatial fixed effects and despite the instrumental variable approach proposed above. A potential solution to this problem is to consider events that shift pollutant concentrations to levels that are not commonly observed and that are unanticipated. I consider episodes of strike in the public transport sector to be such an event and use it as instrument for air pollution levels.

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

[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.

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 health care use only through its influence on pollution levels. I find that pollution levels are indeed correlated with wind speed. Pollution levels in big cities are higher on days with low wind speed, likely because pollution that originated inside the city is carried away on days of high wind speed. It is plausible that the exclusion restriction holds. Common levels of wind speed are unlikely to have a direct effect on health care use. Extremely high wind speed could potentially increase health care 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. I do not find evidence in the data for increased health care use on days of high or exceptionally high wind speed. Similarly, public transport strikes must be sufficiently correlated with air pollution and it must affect health care use only through its influence on pollution levels. I show that pollution levels in the big cities are exceptionally high on days of public transport sector strike. The exclusion restriction for the strike instrument is likely to hold at least 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 trauma surgery), or specialties that are likely to be unresponsive to both the occurrence of strikes or pollution (for example plastic surgery) and serve mainly as placebo.

I use public transport sector strikes and not strikes more generally which means that most people should continue to go to work with the only major change being the use of a different means of transportation to get to their workplace. However, it is possible that some individuals are taking the day off in case it is too difficult to get to their workplace. If these individuals decide to use the newly gained time to go seek for (non-urgent) health care that they would otherwise have looked for at a later moment, then my estimates could pick up this effect rather than the effect of strike-induced pollution. It is unlikely that this happens on a large enough scale for my estimates to be noticeably biased. Still, to further address concerns that the exclusion restriction may not be valid, I run additional IV regressions where I use public transport strikes interacted with wind speed as instrument. The assumption here is that even if strike is not entirely exogenous instrument, the combination of strike and wind speed is exogenous. The effect captured here is the effect of exceptionally high pollution levels on days of public transport strike which also happen to be days of low wind speed relative to strike days with high wind speed and days without strike and high or low wind speed.

Formally, the first stage specification is as follows:

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

where P_{xdp} denotes the measure of pollution of pollutant x on day d in postcode area p, IV_{dp} is an indicator variable equal to one if wind speed is below average on day d in post code area p and zero otherwise.

Alternatively, IV_{dp} is an indicator variable equal to one if a public transport strike occurs on day d in post code area p and zero otherwise. 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 NO2 and O3 pollution and total health care costs. Column 1 shows that each 1 g/m3 increase in daily NO2 (about 7.2% of the mean) is associated with 5.59 Euro of additional health care expenditure the same day which corresponds to a 1.1% increase relative to the average daily health care spending. Each 1 g/m3 increase in daily O3 (about 1.8% of the mean) increases spending by 0.79 Euro or 0.2% relative to the average daily spending. Columns 2 and 3 present the corresponding IV estimates. The estimates from the model using wind as IV imply that each 1 g/m3 increase in daily NO2 causes an increase of 7.57 Euro in aggregate health care spending whereas each each 1 g/m3 in daily O3 causes an increase of 3.94 Euro which translates into an increase of 1.5% and 0.8% relative to the average daily spending. Using strike as instrument yields even larger estimates. Daily spending increases by 21.68 Euros for each 1 g/m3 in NO2 and by 19.68 Euro for each 1 g/m3 in O3. This corresponds to a 4.2% and 3.8% increase in daily spending. The IV estimates are larger than the OLS estimates, suggesting that OLS estimation is biased. Interestingly, OLS regression leads me to underestimate rather than overestimate the effects.

The effects are larger when I restrict the sample to include only the most populated areas. Columns 4 to 6 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 2.7 to 7.6 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 A5 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

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

	Total spending - entire France			Total spending - 70 biggest cities		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	5.59***	7.57***	21.68***	15.08***	24.83**	165.1**
	(0.382)	(1.240)	(2.061)	(2.405)	(9.480)	(58.090)
Effect relative to mean (%)	1.1	1.5	4.2	0.4	0.7	4.6
O3 mean	0.79***	3.94***	19.68***	5.07***	22.10**	157.2***
	(0.057)	(0.591)	(1.947)	(0.711)	(7.566)	(43.999)
Effect relative to mean (%)	0.2	0.8	3.8	0.1	0.6	4.4
Constant	-56.37**			-298.0		
	(19.339)			(383.099)		
Dependent variable mean	513.76	513.76	513.76	3550.96	3550.96	3550.96
Observations	8495951	8484329	6539870	215497	215203	162491
First-stage F-stat		8805.0	3765.3		551.1	162.3

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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.

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 g/m3 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.

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. See Table A6 in the appendix for the first stage using small sample of the 70 biggest cities. I include both O3 and NO2 in the OLS regressions or simultaneously instrument for both pollutants in the IV regressions because there is an inverse relationship between these pollutants and because both pollutants are expected to have independent effects on health (see section 3). The results are qualitatively similar when I only include NO2 in the OLS model and in the strike IV model whereas the results in the wind IV model are not statistically significant anymore. See the section on robustness checks.

[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 A3 and A4 in the appendix.

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

	NO2 mean	O3 mean	PM 10 mean	NO2 mean	O3 mean	PM 10 mean
Low wind speed	3.747***	-7.264***	1.973***			
	(0.026)	(0.025)	(0.018)			
Low wind speed Lag 1	1.526***	-4.300***	1.940***			
	(0.012)	(0.017)	(0.017)			
Low wind speed Lag 2	0.294***	-1.315***	0.943***			
	(0.004)	(0.012)	(0.008)			
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)
Constant	7.334***	85.74***	12.19***	10.64***	80.02***	14.42***
	(0.054)	(0.115)	(0.067)	(0.051)	(0.124)	(0.065)
Observations	8484454	8484454	8484454	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.

5.2 Results by location characteristics

In this section, I present results from heterogeneity analyses based on postcode area characteristics. I separate postcode areas into quantiles according to the value of their Gini Index (measure of inequality ranging from 0 being most equal to 1 being most unequal), unemployment rate and household income. Looking at simple averages of health care spending and pollution levels by postcode characteristics reveals substantial inequalities. Figure A2 to A4 in the appendix present average health care spending and pollution levels for postcode areas separated into deciles. Average health care expenditure varies significantly by postcode area characteristics. Spending is higher in postcode areas that are more unequal and that have a higher unemployment rate. There is no clear income gradient as health care expenditure is high both in the postcode areas from the lowest the highest income decile while spending is lower in the intermedial deciles. Average NO2 pollution levels also vary substantially. Average NO2 pollution is higher in more unequal postcode areas. The relation between average NO2 pollution and average postcode area unemployment level is u-shaped with higher pollution levels in low unemployment areas and high unemployment areas. Average NO2 pollution levels drop from the first to the second income decile and then monotonously increase. NO2 levels are as high in the first income decile as in the 7th income decile. The differences in average O3 and PM pollution are much less marked.

For the regressions, I separate postcode areas into quintiles according to their average Gini Index, unemployment rate and household income, respectively. I find evidence of substantial heterogeneity, with the most disadvantaged regions being more heavily affected. Panels A and B in Table 3 present the estimates from the wind IV and strike IV model, respectively, by Gini Index quintiles. The increase in healthcare spending for a 1 g/m3 increase in daily NO2 or O3 is 4 to 6 times stronger in the most unequal postcode area compared to the most equal quintile. However, the effect relative to the mean is relatively similar or even feebler in the most unequal quintiles because health care spending is on average higher in more unequal postcode areas. Panels C and D present results by unemployment rate quintiles. The effects are in between 1.4 to 2.1 times stronger in the postcode area quintile with the highest unemployment rate compared to the postcode area with the lowest unemployment rate. Yet again, the effect relative to the mean is similar between the first and last quintile because of the higher average health care spending in the postcode areas with the highest unemployment rates compared to the areas with the lowest unemployment rates.

Tables A7 to A12 in the appendix show all results including coefficients from OLS regressions by Gini Index, unemployment rate and income quintiles for the whole sample and the sample including the 10% most populated postcode areas. The results by Gini Index and unemployment rate are qualitatively similar to what has been presented in Table 3. The effects by income quintiles are not conclusive (Tables A9 and A12). The results for the smaller sample of the 70 biggest cities are mostly not statistically significant and are therefore not shown.

Separating the sample into quintiles according to average pollution levels leads to ambiguous results (see Tables A13 and A14 in the appendix).

Table 3: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area Gini Index and unemployment quintiles (whole sample)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
***Panel A**: Wind IV, heterogeneity by Gini Index quintile (1st quintile is most equal)*					
NO2 mean	5.386**	9.364***	4.940*	9.412***	20.08***
	(2.004)	(2.570)	(2.419)	(2.781)	(3.998)
Effect relative to mean (%)	1.5	2.0	0.9	1.4	1.3
O3 mean	2.423**	4.872***	3.056*	5.643***	14.42***
	(0.892)	(1.216)	(1.280)	(1.512)	(2.602)
Effect relative to mean (%)	0.7	1.1	0.6	0.9	1.0
Dependent variable mean	349.3	461.02	526.54	658.89	1505.1
Observations	1157331	1086203	1115756	1073445	1032594
First-stage F-stat	1877.0	1462.5	1572.2	1397.7	1479.6
***Panel B**: Strike IV, heterogeneity by Gini Index quintile (1st quintile is most equal)*					
	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	20.65***	14.96***	21.80***	29.90***	52.13***
	(4.314)	(4.205)	(4.824)	(4.737)	(8.566)
Effect relative to mean (%)	5.9	3.2	4.1	4.5	3.5
O3 mean	5.256*	15.59***	20.66***	14.67***	32.49***
	(2.457)	(3.855)	(3.813)	(3.677)	(6.833)
Effect relative to mean (%)	1.5	3.4	3.9	2.2	2.2
Dependent variable mean	349.3	461.02	526.54	658.89	1505.1
Observations	1158917	1087691	1117284	1074915	1034008
First-stage F-stat	501.2	403.3	461.3	457.4	502.2
***Panel C**: Wind IV, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)*					
	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	6.142***	12.60***	10.77**	10.23*	8.902*
	(1.827)	(2.628)	(3.420)	(4.771)	(3.715)
Effect relative to mean (%)	1.1	2.2	1.7	1.3	1.0
O3 mean	3.512***	7.066***	5.933***	6.036*	5.761**
	(0.951)	(1.342)	(1.632)	(2.508)	(2.215)
Effect relative to mean (%)	0.6	1.2	0.9	0.7	0.6
Dependent variable mean	549.83	583.04	634.71	804.82	915.47
Observations	1314531	1000127	977515	1120134	1053022
First-stage F-stat	1528.6	1140.1	1150.9	1348.6	1604.3
***Panel D**: Strike IV, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)*					
	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	20.93***	26.74***	24.17***	34.52***	44.88***
	(4.933)	(5.357)	(6.133)	(7.786)	(6.747)
Effect relative to mean (%)	3.8	4.6	3.8	4.3	4.9
O3 mean	15.69***	15.49***	9.346*	19.35***	26.24***
	(3.272)	(3.918)	(4.362)	(5.336)	(5.448)
Effect relative to mean (%)	2.9	2.7	1.5	2.4	2.9
Dependent variable mean	549.83	583.04	634.71	804.82	915.47
Observations	1316331	1001497	978855	1121668	1054464
First-stage F-stat	537.1	393.4	340.5	450.9	584.0

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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.

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. Tables A15 to A16 in the appendix show 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. Finding effects in all age groups could be explained by the fact that I am looking at overall health care costs, which include the costs of treating milder health consequences that are likely to occur in all age groups, whereas a study of the impact on mortality might have revealed that the effects are concentrated in the young and the old, with mortality being a rather extreme outcome likely to affect only the most vulnerable.

I further explore whether individuals with preexisting health conditions are more vulnerable to pollution exposure by dividing the sample into those who have a chronic disease and those who do not. This investigation remains inconclusive. The results from the OLS and wind IV regressions suggest that the effect of pollution health care spending are stronger for individuals with a chronic disease. The results from the strike IV, however, point in the opposite direction. See Table A18 in the appendix. Finally, I investigate whether effects differ for individuals who are covered by the CMUc (*Couverture mdicale universelle complmentaire*), a state funded complementary insurance plan available to low-income individuals. I use this information to approximate socioeconomic status (SES), supposing that coverage by CMUc indicates low SES. I do not find that individuals who are covered by the CMUc are affected more than individuals covered by regular insurance plans. Table A19 in the appendix shows that the effect relative to the average spending of the two groups is similar.

5.4 Results by medical specialty

I examine what types of health conditions are affected by exposure to air pollution by running separate regressions for 15 different categories of medical specialties. While interesting in its own right, this exercise also serves as a sanity check. I consider both medical specialties that should be affected by air pollution and medical specialties 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, pneumology, neurology, genecology, abmulance services. The placebo specialties include gastro-hepatology, rhumatology, nephrology and plastic surgery.

Table A20 shows the OLS results by medical specialty for the entire sample. All estimates, including the estimates for the placebo categories, are positive and statistically significant. Finding that all medical categories including specialties such as rhumatology, nephrology and plastic surgery are affected suggests that there might be an issue with spurious correlation. This could happen, for example, if the day of the week effects do not allow to correctly account for the co-movements of pollution and health care activity across the week. The estimates on the placebo medical specialties become smaller and statistically not significant when I restrict the sample to the 10% most populated cities and the sample including only the 70 biggest cities (with the notable exception of plastic surgery, see Tables A21 to A22). The cyclical movements of pollution and medical activity could differ across locations in a way that a day of the week fixed effect that is common to all observations cannot account for. This hypothesis is supported by the results from regressions where I interact a dummy indicating that the day is a weekday with the location fixed effect to allow weekly cyclical movements to vary by postcode area (Tables A23 and A24[10]). I find that most of the coefficients on the placebo medical categories are less statistically significant or not significant anymore.

Results by medical specialty for the model using strike as instrument for air pollution are reported in Tables A25 to A29 in the appendix. The strike IV seems to at least partially address the problem of the spurious correlations. Even for the regressions on the whole sample and without interaction the weekday fixed effect with the location fixed effects, the coefficients on the placebo categories rhumatology, nephrology, and gastro-hepatology are not statistically significant. The coefficient on plastic surgery is statistically significant at the 5% level. The effect on plastic surgery disappears for all other samples and the models included interacted weekday and location fixed effects. Trauma surgery should be unrelated to pollution exposure, yet the IV estimate is positive and statistically significant, probably pointing toward the limitation of using public transport strikes as instrument for air pollution exposure. Public transport strikes may have an impact on the number of accidents due to increased car traffic and, therefore, increase trauma surgery expenses, independently of their effect on pollution. Surprisingly, the coefficients on the medical specialties pneumology are not significant. I find that the results are most robust for the categories otorhinolaryngology, ophthalmology, dentistry, neurology, genecology, and abmulance services. Similar to the effects for health expenditure at the aggregate level, the IV estimates are generally larger than the OLS estimates. Estimates for the wind IV are reported in Tables A30 to A34 in the appendix. Mostly only the estimates for family medicine and ambulance services are statistically significant. The wind IV approach is likely the more conservative approach to be taken.

5.5 Robustness checks

The results are robust to alternative model specifications with different time fixed effect structures and weather controls. Table A35 in the appendix shows the main estimates of the relationship between daily NO2 and O3 pollution and total health care costs when I use month and year fixed effects rather than month-by-department and month-by-year fixed effects. The results are almost identical to the estimates from my preferred model specification shown in Table 1. Table A37 and Table A38 in the appendix show the main estimates for models excluding the vector of temperature and precipitation bins with full time fixed effects and simpler time fixed effects. However, accounting for cyclical movements in pollution and health care use across the week appears to be important. Excluding the day of the week fixed effects leads to estimates that are about 3 times larger compared to the estimates from models including the full range of time fixed effects, as shown in Table A36. The results are also robust to using different lag structures for the pollutants and weather controls (Table Table A39 in the appendix). Tables A40 and A41 in the appendix show that results are robust to using different definitions of the strike IV (a dummy equal to 1 for any day of strike, dummies for the first, second and third day of strike, etc.), but less robust to using different definitions constructions for the wind IV (dummy for low wind speed, dummies for the lag of wind speed or wind speed).

[10]Results for the entire sample are not available yet due to lack of computation power.

I observe important correlations between the pollutants. Both NO2 and particulate matter and O3 are generally inversely related while NO2 and PM are positively correlated (see again section 2). Due to the systematic co-movements, I cannot estimate separately the effects for PM and 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. Still, I examine whether the effects of NO2 and O3 are robust to the inclusion of additional controls for particulate matter (PM10 and PM2.5) pollution. Table A42 in the appendix shows that the results remain qualitatively the same. 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 PM10 and PM2.5 pollution increases health care spending but the effects are far less pronounced than the effects from NO2 pollution (Table A43 in the appendix). I include O3 together with either NO2 or PM in all regressions to avoid underestimating the effects of a pollutant because an increase of NO2 or PM that could lead to adverse health effects systematically coincides with a decrease of O3 which could yield health benefits. The results are not entirely robust when I look only at one pollutant without simultaneously instrumenting or at least controlling for the other observed pollutants. See Table A44 for the estimates considering only one pollutant at a time.

5.6 Extensions

In further extensions of this work, I estimate the effect of air pollution on mortality, and on sick leave. Preliminary results suggest that higher in NO2 and O3 pollution leads to an increase in the number of sick days taken and increases the costs to the health care system due to sick leave payments. See Table A45 in the appendix. The results regarding mortality are not yet conclusive. I find a small effect of increased mortality when NO2 and O3 levels are higher using OLs regressions, but the results for the IV regressions are not statistically significant (Table A46 in the appendix).

I continue my investigation by exploring 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 local pollution emissions). I interact dummies for the daily average wind direction by 90-degree intervals with a dummy for the postcode area to allow the wind direction instrument to vary by location. This is very similar to the IV model 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. 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. Using wind direction as instrument yields estimates of a magnitude similar to the estimates from the strike IV models. Using thermal inversions as instrument only yields results that are borderline statistically significant. See Table A47 in the appendix.

6 Discussion

This study presents evidence of non-negligible health care costs caused by exposure to pollution levels that are mostly below current legal limits. I estimate that each 1 g/m3 increase in daily NO2 (7.2% of the mean) cause an increase of €7.57 in aggregate health care spending whereas each each 1 g/m3 in daily O3 (1.8% of the mean) causes an increase of €3.94 which translates into an increase of 1.5% and 0.8% relative to the average daily spending. These are relatively conservative estimates, as many model specifications yield 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.

6.1 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 health care 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 health care costs due to the decreased NO2 pollution alone sets off 40% 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 $€7.57 \cdot 97 \cdot 365 \cdot 6,048 = €1,620,959,861$ health care spending per year. Similarly, the €3.94 increase in spending related to a 1 $\mu g/m^3$ increase in daily O3 translates into $€3.94 \cdot 97 \cdot 365 \cdot 6,048 = €843,669,994$ health care 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.

6.2 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 health care) 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 health care costs in France. The evaluation of health care 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 health care system. The result was a report on two studies that considered only a fraction of the total health care 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 health care 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 air pollution levels. In addition, these studies estimate the health care 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 health care costs linked to air pollution which is estimated at €4.7 billion per year for the scenario of 2005 pollution levels and €2.3 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 health care costs at EU level is therefore estimated at only €2.4 billion per year which is much smaller than the benefits

[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

that I estimate for France alone. The total reduction in NO2 concentrations by 8.75 $\mu g/m^3$ from 2005 pollution levels in should allow savings of €14 billion annually in France alone.[16] The health care 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 health care 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 health care costs have been underestimated to date. Other studies that quantify health care 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.

6.3 Limitations

While the data on health care reimbursements from the French National System of Health Data provides a great detail of information concerning health care on the nature of medical acts and associated costs of treatment for all types of health care and some basic information on patient characteristics, it does not include any information on patient socioeconomic status. The level of education, income and socioprofessional category have been proven to influence health care consumption and health status. It is important to remember that the 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 make some inferences about socioeconomic status based on whether the individual qualifies for free public complementary health insurance and I analyse effect heterogeneity by location characteristics as proxy for certain 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

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

not observe any health care 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 implicitly assume that the place of residence as reported in the health care data set corresponds to the usual place where the individual is exposed to pollution. 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. I observe only the most recent place of residence and do not observe whether individuals have moved in the past.[17] This should hopefully concern only a small fraction of the sample but pollution exposure is likely to be wrongly assigned for this group and could lead my estimates to be biased toward zero (attenuation bias).

Finally, this study only considers the health care 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.

6.4 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).[18] 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 $\mu g/m^3$ for PM2.5 from 25 $\mu g/m^3$ to 10 $\mu g/m^3$. However, this study provides evidence for sizeable health care 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 health care 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] The only information that could possibly identify whether individuals have moved is the change of affiliation to the primary health insurance fund (CPAM). There are only 102 CPAMs in metropolitan France, which means that identifying moves from changes in CPAM is clearly not sufficient to detect moves at a sufficiently fine geographic resolution.

[18] `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.

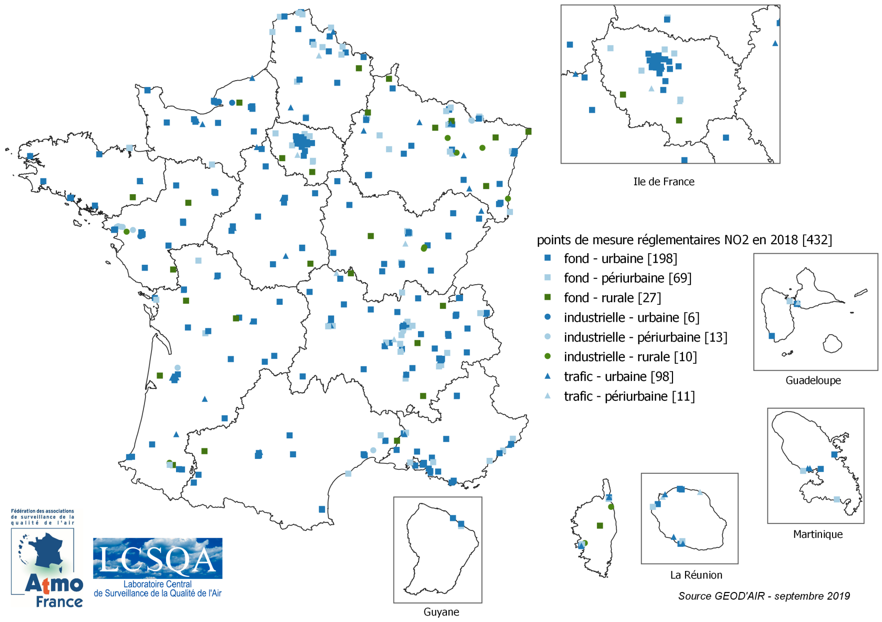

Figure A1: Map of the spatial distribution of NO2 measuring stations in France. *Source: GEOD'AIR available here.*

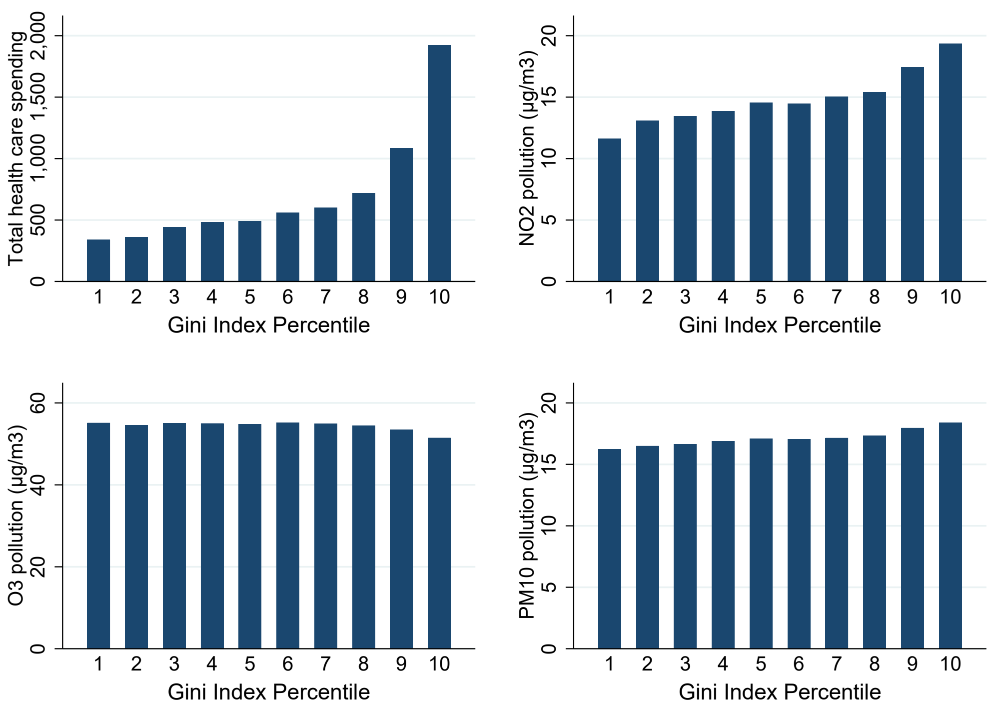

Figure A2: Mean of health care spending and pollutants by postcode area Gini Index deciles.

Table A2: 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
Pneumology	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
Duration of strike at postcode area level	33.51	29.76	1	108	4664
Distance to nearest postcode area with strike	389.21	218.74	0	1326	5757696
Strike at department level = 1	0.04	0.19	0	1	8836128
Duration of strike at department level	13.13	10.88	1	43	339148
Strike at national level = 1	0.25	0.44	0	1	8836128
Duration of strike at national level	56.08	27.06	1	87	2249856
Percentage of SNCF personnel striking	5.4	4.2	0.2	11.5	1149120
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 A3: 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
Pneumology	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
Duration of strike at postcode area level	34.83	30.55	1	108	4277
Distance to nearest postcode area with strike	378.83	215.31	0	1264	575008
Strike at department level = 1	0.05	0.22	0	1	882444
Duration of strike at department level	13	10.54	1	43	47115
Strike at national level = 1	0.25	0.44	0	1	882444
Duration of strike at national level	56.08	27.06	1	87	224688
Percentage of SNCF personnel striking	5.4	4.2	0.2	11.5	114760
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 A4: 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
Pneumology	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
Duration of strike at postcode area level	32.52	28.9	1	108	3933
Distance to nearest postcode area with strike	388.97	224.93	0	1257	157080
Strike at department level = 1	0.05	0.23	0	1	241065
Duration of strike at department level	12.87	10.32	1	35	12904
Strike at national level = 1	0.25	0.44	0	1	241065
Duration of strike at national level	56.08	27.06	1	87	61380
Percentage of SNCF personnel striking	5.4	4.2	0.2	11.5	31350
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

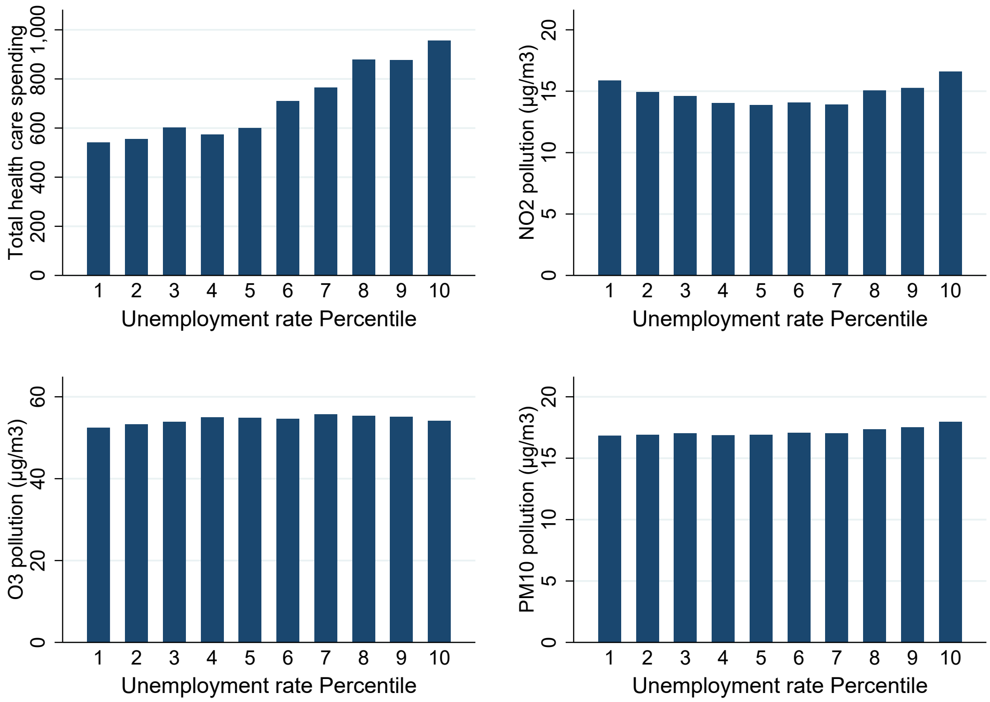

Figure A3: Mean of health care spending and pollutants by postcode area unemployment rate deciles.

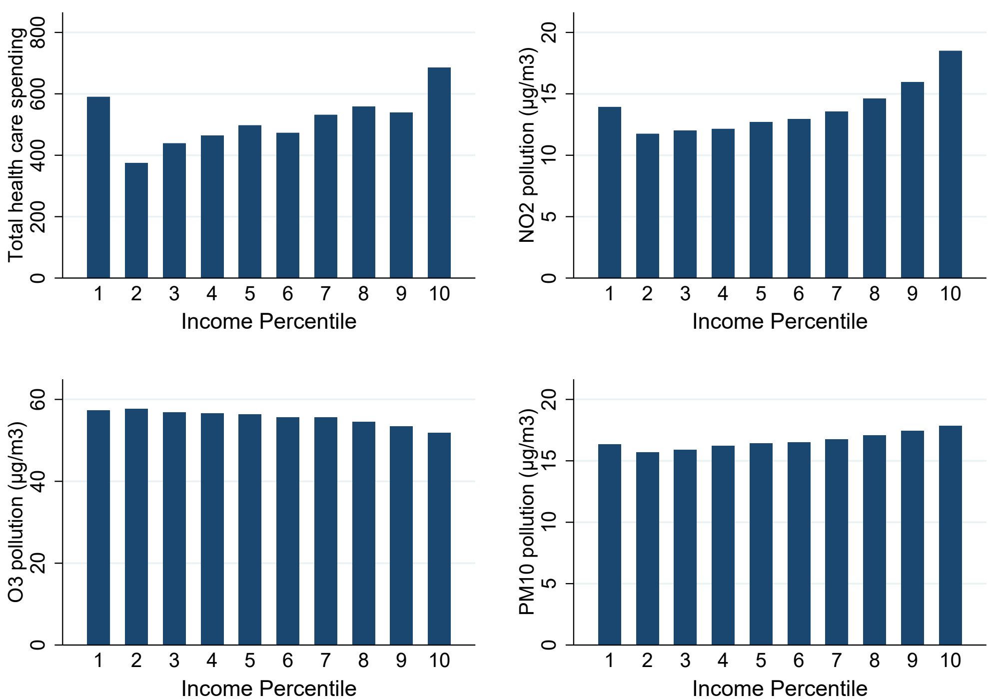

Figure A4: Mean of health care spending and pollutants by postcode area income deciles.

Table A5: OLS and IV Estimates of Effect of NO2 and O3 on Health Care Expenditure

	Spending - 10% most populated areas		
	OLS	Wind IV	Strike IV
	(1)	(2)	(3)
NO2 mean	9.951***	23.98***	105.8***
	(1.129)	(3.726)	(25.456)
Effect relative to mean (%)	0.5	1.1	4.9
O3 mean	2.607***	17.88***	103.6***
	(0.282)	(2.487)	(17.050)
Effect relative to mean (%)	0.1	0.8	4.8
Constant	-99.09		
	(123.356)		
Dependent variable mean	2162.65	2162.65	2162.65
Observations	837876	836730	637450
First-stage F-stat		1356.1	424.8

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

Table A6: First stage regressions corresponding to the IV regressions shown in Table 1 for the sample of the 70 biggest cities

	NO2 mean	O3 mean	PM 10 mean	NO2 mean	O3 mean	PM 10 mean
Low wind speed	7.131***	-8.136***	3.193***			
	(0.177)	(0.201)	(0.108)			
Low wind speed lag 1	2.488***	-4.708***	2.699***			
	(0.091)	(0.124)	(0.099)			
Low wind speed lag 2	0.125***	-1.306***	1.069***			
	(0.029)	(0.081)	(0.044)			
Strike day 1				0.274***	0.147	-0.258***
				(0.076)	(0.093)	(0.058)
Strike day 2				1.645***	-1.732***	0.260
				(0.076)	(0.159)	(0.132)
Strike day 3				1.206***	-2.681***	-0.403***
				(0.114)	(0.188)	(0.114)
Constant	15.53***	73.92***	12.63***	20.14***	68.97***	15.39***
	(0.385)	(0.560)	(0.488)	(0.429)	(0.579)	(0.514)
Observations	215203	215203	215203	162491	162491	162491

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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 A7: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area Gini Index quintiles (whole sample)

OLS regression, heterogeneity by Gini Index quintile (1st quintile is most equal)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	1.255***	2.394***	2.174***	4.581***	13.09***
	(0.220)	(0.310)	(0.361)	(0.496)	(1.374)
Effect relative to mean (%)	0.36	0.52	0.41	0.70	0.87
O3 mean	0.0906	0.468***	0.351***	0.596***	2.304***
	(0.062)	(0.095)	(0.103)	(0.120)	(0.303)
Effect relative to mean (%)	0.03	0.10	0.07	0.09	0.15
Constant	35.50**	30.00	34.11	1.282	22.23
	(13.034)	(19.061)	(20.203)	(31.029)	(103.696)
Dependent variable mean	349.3	461.02	526.54	658.89	1505.1
Observations	1155743	1084711	1114222	1071969	1031174

Wind IV regression, heterogeneity by Gini Index quintile (1st quintile is most equal)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	5.386**	9.364***	4.940*	9.412***	20.08***
	(2.004)	(2.570)	(2.419)	(2.781)	(3.998)
Effect relative to mean (%)	1.5	2.0	0.9	1.4	1.3
O3 mean	2.423**	4.872***	3.056*	5.643***	14.42***
	(0.892)	(1.216)	(1.280)	(1.512)	(2.602)
Effect relative to mean (%)	0.7	1.1	0.6	0.9	1.0
Dependent variable mean	349.3	461.02	526.54	658.89	1505.1
Observations	1157331	1086203	1115756	1073445	1032594
First-stage F-stat	1877.0	1462.5	1572.2	1397.7	1479.6

Strike IV regression, heterogeneity by Gini Index quintile (1st quintile is most equal)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	20.65***	14.96***	21.80***	29.90***	52.13***
	(4.314)	(4.205)	(4.824)	(4.737)	(8.566)
Effect relative to mean (%)	5.9	3.2	4.1	4.5	3.5
O3 mean	5.256*	15.59***	20.66***	14.67***	32.49***
	(2.457)	(3.855)	(3.813)	(3.677)	(6.833)
Effect relative to mean (%)	1.5	3.4	3.9	2.2	2.2
Dependent variable mean	349.3	461.02	526.54	658.89	1505.1
Observations	1158917	1087691	1117284	1074915	1034008
First-stage F-stat	501.2	403.3	461.3	457.4	502.2

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A8: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area unemployment quintiles (whole sample)

OLS regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	6.467***	5.286***	5.593***	9.589***	10.85***
	(1.104)	(1.126)	(0.744)	(1.960)	(1.218)
Effect relative to mean (%)	1.2	0.9	0.9	1.2	1.2
O3 mean	1.025***	0.737***	0.916***	1.259***	1.387***
	(0.178)	(0.179)	(0.155)	(0.324)	(0.213)
Effect relative to mean (%)	0.19	0.13	0.14	0.16	0.15
Constant	37.89	49.39	10.60	-11.84	56.45
	(29.548)	(29.289)	(34.872)	(76.235)	(59.862)
Dependent variable mean	549.83	583.04	634.71	804.82	915.47
Observations	1312723	998753	976175	1118594	1051574

Wind IV regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	6.142***	12.60***	10.77**	10.23*	8.902*
	(1.827)	(2.628)	(3.420)	(4.771)	(3.715)
Effect relative to mean (%)	1.1	2.2	1.7	1.3	1.0
O3 mean	3.512***	7.066***	5.933***	6.036*	5.761**
	(0.951)	(1.342)	(1.632)	(2.508)	(2.215)
Effect relative to mean (%)	0.6	1.2	0.9	0.7	0.6
Dependent variable mean	549.83	583.04	634.71	804.82	915.47
Observations	1314531	1000127	977515	1120134	1053022
First-stage F-stat	1528.6	1140.1	1150.9	1348.6	1604.3

Strike IV regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	20.93***	26.74***	24.17***	34.52***	44.88***
	(4.933)	(5.357)	(6.133)	(7.786)	(6.747)
Effect relative to mean (%)	3.8	4.6	3.8	4.3	4.9
O3 mean	15.69***	15.49***	9.346*	19.35***	26.24***
	(3.272)	(3.918)	(4.362)	(5.336)	(5.448)
Effect relative to mean (%)	2.9	2.7	1.5	2.4	2.9
Dependent variable mean	549.83	583.04	634.71	804.82	915.47
Observations	1316331	1001497	978855	1121668	1054464
First-stage F-stat	537.1	393.4	340.5	450.9	584.0

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A9: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area income quintiles (whole sample)

OLS regression, heterogeneity by income quintile (1st quintile is lowest income)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	10.67***	7.607***	6.705***	5.383***	5.968***
	(1.178)	(1.407)	(1.535)	(0.933)	(0.813)
Effect relative to mean (%)	2.21	1.68	1.38	0.99	0.97
O3 mean	0.981***	0.873***	0.763***	0.596***	1.055***
	(0.158)	(0.172)	(0.213)	(0.141)	(0.149)
Effect relative to mean (%)	0.20	0.19	0.16	0.11	0.17
Constant	25.02	5.155	13.98	28.98	41.71
	(38.252)	(38.465)	(36.828)	(28.646)	(30.022)
Dependent variable mean	482.9	451.93	485.6	545.4	612.6
Observations	1723605	1685361	1693730	1664954	1664227

Wind IV regression, heterogeneity by income quintile (1st quintile is lowest income)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	4.973	1.691	11.58**	9.599***	8.523***
	(3.871)	(3.207)	(3.635)	(2.743)	(1.566)
Effect relative to mean (%)	1.0	0.4	2.4	1.8	1.4
O3 mean	2.327	1.171	5.422***	4.948***	5.483***
	(1.713)	(1.280)	(1.589)	(1.330)	(0.941)
Effect relative to mean (%)	0.5	0.3	1.1	0.9	0.9
Dependent variable mean	482.9	451.93	485.6	545.4	612.6
Observations	1725977	1687673	1696064	1667250	1666513
First-stage F-stat	1519.9	1743.7	2037.9	2399.4	3580.4

Strike IV regression, heterogeneity by income quintile (1st quintile is lowest income)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	18.15***	21.19***	25.61***	22.36***	23.40***
	(4.857)	(5.259)	(5.688)	(4.149)	(4.248)
Effect relative to mean (%)	3.8	4.7	5.3	4.1	3.8
O3 mean	14.68***	7.036*	10.22***	16.47***	17.77***
	(3.902)	(3.209)	(2.978)	(3.344)	(2.857)
Effect relative to mean (%)	3.0	1.6	2.1	3.0	2.9
Dependent variable mean	482.9	451.93	485.6	545.4	612.6
Observations	1728341	1689987	1698386	1669532	1668797
First-stage F-stat	859.7	782.8	683.8	663.9	735.2

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area Gini Index quintiles (10% most populated postcode areas sample)

OLS regression, heterogeneity by Gini Index quintile (1st quintile is most equal)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	3.149**	6.132***	4.459***	13.61***	14.84***
	(0.995)	(1.170)	(1.307)	(2.569)	(3.326)
Effect relative to mean (%)					
O3 mean	0.623	1.606***	0.910	3.267***	4.155***
	(0.396)	(0.411)	(0.523)	(0.809)	(1.064)
Effect relative to mean (%)					
Constant	139.9*	-57.02	15.02	221.4	-25.50
	(67.603)	(105.923)	(127.333)	(227.060)	(493.321)
Dependent variable mean					
Observations	174838	167554	174474	157355	159902

Wind IV regression, heterogeneity by Gini Index quintile (1st quintile is most equal)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	21.96***	20.33***	24.18***	26.23**	27.69*
	(6.646)	(6.054)	(6.452)	(8.145)	(11.043)
Effect relative to mean (%)					
O3 mean	13.11***	13.57***	19.33***	18.68***	26.04**
	(3.418)	(3.710)	(4.618)	(5.338)	(8.997)
Effect relative to mean (%)					
Dependent variable mean					
Observations	175078	167784	174712	157571	160126
First-stage F-stat	287.8	233.5	340.6	247.4	442.9

Strike IV regression, heterogeneity by Gini Index quintile (1st quintile is most equal)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	66.80**	91.36**	71.13*	155.0***	183.0***
	(25.557)	(29.383)	(31.713)	(35.218)	(42.606)
Effect relative to mean (%)					
O3 mean	71.46	78.39*	16.41	212.3***	86.93
	(39.680)	(30.974)	(32.102)	(57.663)	(54.543)
Effect relative to mean (%)					
Dependent variable mean					
Observations	175318	168014	174952	157787	160344
First-stage F-stat	46.07	80.86	112.5	88.94	139.2

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A11: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area unemployment quintiles (10% most populated postcode areas sample)

OLS regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	12.54***	7.472***	11.46**	12.75**	9.585***
	(2.575)	(2.006)	(3.618)	(3.848)	(2.115)
Effect relative to mean (%)	0.60	0.45	0.54	0.52	0.39
O3 mean	2.819***	1.820***	1.916*	2.718*	1.868**
	(0.609)	(0.518)	(0.769)	(1.076)	(0.705)
Effect relative to mean (%)	0.13	0.11	0.09	0.11	0.08
Constant	146.3	73.31	70.61	-122.6	87.84
	(164.271)	(128.023)	(280.321)	(393.927)	(273.052)
Dependent variable mean	2095.4	1655.6	2122.2	2438.5	2463.3
Observations	195232	150433	165735	160270	162453

Wind IV regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	24.42***	22.62**	39.14***	17.21	17.47*
	(4.693)	(7.318)	(11.555)	(13.226)	(6.802)
Effect relative to mean (%)	1.2	1.4	1.8	0.7	0.7
O3 mean	19.63***	14.96***	25.52***	12.32	15.03**
	(3.422)	(3.827)	(6.564)	(8.329)	(5.622)
Effect relative to mean (%)	0.9	0.9	1.2	0.5	0.6
Dependent variable mean	2095.4	1655.6	2122.2	2438.5	2463.3
Observations	195500	150641	165961	160490	162679
First-stage F-stat	325.9	192.9	249.2	271.4	679.1

Strike IV regression, heterogeneity by unemployment quintile (1st quintile is lowest unemployment)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	128.8***	115.1***	97.50**	150.2***	144.8***
	(32.037)	(34.177)	(33.598)	(40.856)	(36.084)
Effect relative to mean (%)	6.1	7.0	4.6	6.2	5.9
O3 mean	109.8***	151.6**	30.90	94.03	92.29*
	(31.645)	(46.640)	(36.174)	(55.345)	(41.614)
Effect relative to mean (%)	5.2	9.2	1.5	3.9	3.7
Dependent variable mean	2095.4	1655.6	2122.2	2438.5	2463.3
Observations	195768	150847	166189	160710	162901
First-stage F-stat	91.43	51.43	65.83	80.39	143.0

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A12: Effects of NO2 and O3 on total health care spending - heterogeneous effects by postcode area income quintiles (10% most populated postcode areas sample)

OLS regression, heterogeneity by income quintile (1st quintile is lowest income)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	5.816**	14.46***	18.30**	8.594**	11.66***
	(1.739)	(3.598)	(6.155)	(3.057)	(2.176)
Effect relative to mean (%)	0.2	0.6	1.0	0.5	0.5
O3 mean	1.506	2.343**	3.394**	1.520*	3.102***
	(0.809)	(0.699)	(1.234)	(0.677)	(0.613)
Effect relative to mean (%)	0.06	0.10	0.18	0.08	0.14
Constant	-63.22	61.73	23.78	19.16	236.2
	(327.423)	(266.431)	(304.957)	(181.253)	(179.065)
Dependent variable mean	2594.0	2298.2	1843.3	1878.1	2204.6
Observations	166461	160269	170104	166096	171193

Wind IV regression, heterogeneity by income quintile (1st quintile is lowest income)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	24.20**	15.75	27.36*	27.56**	23.36***
	(8.741)	(10.302)	(13.336)	(8.564)	(4.330)
Effect relative to mean (%)	0.93	0.69	1.48	1.47	1.06
O3 mean	20.49**	11.61	15.72*	18.81***	20.98***
	(6.736)	(6.160)	(6.725)	(5.163)	(3.598)
Effect relative to mean (%)	0.79	0.51	0.85	1.00	0.95
Dependent variable mean	2594.0	2298.2	1843.3	1878.1	2204.6
Observations	166691	160489	170336	166324	171431
First-stage F-stat	621.3	194.7	231.7	250.1	562.9

Strike IV regression, heterogeneity by income quintile (1st quintile is lowest income)

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	148.4***	120.4***	103.8**	145.7***	138.1***
	(38.811)	(31.661)	(38.836)	(39.259)	(32.454)
Effect relative to mean (%)	5.7	5.2	5.6	7.8	6.3
O3 mean	139.8*	77.94	41.67	118.5**	100.5**
	(58.607)	(48.570)	(44.333)	(39.745)	(32.237)
Effect relative to mean (%)	5.4	3.4	2.3	6.3	4.6
Dependent variable mean	2594.0	2298.2	1843.3	1878.1	2204.6
Observations	166919	160709	170570	166552	171665
First-stage F-stat	168.7	71.68	44.17	95.86	71.47

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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 A13: Effects of NO2 and O3 on total health care spending - heterogeneous effects by NO2 pollution quintiles (whole sample)

OLS regression, heterogeneity by average postcode NO2 quintile

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	2.448***	2.397***	2.241***	2.126***	6.878***
	(0.284)	(0.250)	(0.266)	(0.383)	(0.654)
Effect relative to mean (%)	0.8	0.7	0.6	0.4	0.6
O3 mean	0.220**	0.270***	0.231**	0.241*	1.462***
	(0.068)	(0.057)	(0.071)	(0.108)	(0.174)
Effect relative to mean (%)	0.1	0.1	0.1	0.05	0.1
Constant	15.55	-2.228	25.86	0.413	46.88
	(11.338)	(15.458)	(18.352)	(28.003)	(63.254)
Dependent variable mean	302.27	326.20	391.61	488.59	1061.75
Observations	1628872	1716686	1720701	1723613	1682801

Wind IV regression, heterogeneity by average postcode NO2 quintile

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	8.298***	10.79***	7.149*	8.046***	8.172***
	(2.461)	(2.980)	(3.395)	(2.359)	(1.851)
Effect relative to mean (%)	2.7	3.3	1.8	1.6	0.8
O3 mean	2.963***	4.001***	3.084*	4.522***	6.469***
	(0.791)	(1.011)	(1.441)	(1.225)	(1.308)
Effect relative to mean (%)	1.0	1.2	0.8	0.9	0.6
Dependent variable mean	302.27	326.20	391.61	488.59	1061.75
Observations	1631126	1719044	1723063	1725979	1685117
First-stage F-stat	6228.4	7247.0	7936.0	7967.0	7846.2

Strike IV regression, heterogeneity by average postcode NO2 quintile

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	2.089	23.83***	21.13***	24.83***	35.69***
	(7.447)	(5.099)	(3.921)	(4.393)	(4.949)
Effect relative to mean (%)	0.7	7.3	5.4	5.1	3.4
O3 mean	10.41***	1.520	4.816*	13.11***	27.58***
	(2.966)	(2.433)	(2.403)	(2.638)	(3.963)
Effect relative to mean (%)	3.4	0.5	1.2	2.7	2.6
Dependent variable mean	302.27	326.20	391.61	488.59	1061.75
Observations	1633356	1721400	1725425	1728345	1687425
First-stage F-stat	1519.0	1773.8	1421.6	820.0	1130.5

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A14: Effects of NO2 and O3 on total health care spending - heterogeneous effects by NO2 pollution quintiles (10% most populated postcode areas)

OLS regression, heterogeneity by average postcode NO2 quintile

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	9.854***	8.429**	8.963***	4.829**	6.531***
	(1.763)	(3.085)	(2.221)	(1.517)	(1.414)
Effect relative to mean (%)	0.6	0.4	0.5	0.2	0.2
O3 mean	1.453**	1.388	2.197***	1.614	3.503***
	(0.451)	(0.860)	(0.553)	(0.889)	(0.638)
Effect relative to mean (%)	0.09	0.07	0.12	0.07	0.11
Constant	23.90	-6.857	-27.16	-64.34	141.6
	(98.080)	(206.245)	(194.807)	(394.039)	(323.432)
Dependent variable mean	1540.25	1971.63	1803.89	2414.08	3057.84
Observations	170465	167555	169011	159538	169011

Wind IV regression, heterogeneity by average postcode NO2 quintile

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	49.29***	27.61*	17.30	22.61**	23.75***
	(10.244)	(14.043)	(10.700)	(8.329)	(3.957)
Effect relative to mean (%)	3.2	1.4	1.0	0.9	0.8
O3 mean	21.25***	16.35*	11.45	21.17**	26.30***
	(3.799)	(7.060)	(6.444)	(6.552)	(4.412)
Effect relative to mean (%)	1.38	0.83	0.63	0.88	0.86
Dependent variable mean	1540.25	1971.63	1803.89	2414.08	3057.84
Observations	170699	167785	169243	159760	169243
First-stage F-stat	720.2	732.2	1003.1	2323.7	4411.4

Strike IV regression, heterogeneity by average postcode NO2 quintile

	Total spent - 1st quintile	Total spent - 2nd quintile	Total spent - 3rd quintile	Total spent - 4th quintile	Total spent - 5th quintile
NO2 mean	45.27	178.3***	132.8***	107.4**	136.5***
	(88.169)	(35.451)	(37.785)	(36.894)	(37.466)
Effect relative to mean (%)	2.9	9.0	7.4	4.4	4.5
O3 mean	70.74	68.96	105.0**	41.79	129.1***
	(53.270)	(58.881)	(35.079)	(48.864)	(34.000)
Effect relative to mean (%)	4.6	3.5	5.82	1.7	4.2
Dependent variable mean	1540.25	1971.63	1803.89	2414.08	3057.84
Observations	170933	168015	169475	159978	169475
First-stage F-stat	72.24	82.21	72.13	130.0	241.1

* p<0.05, ** p<0.01, *** p<0.001

Note: 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 A15: Impact of pollution on health care expenditure by age, OLS model (entire sample)

	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
Constant	1.008	1.000	-1.064	4.521*	-9.476***
	(1.196)	(1.593)	(1.066)	(2.047)	(2.497)
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
Constant	9.516**	-11.67***	-10.41***	4.445	1.960*
	(3.109)	(2.519)	(2.290)	(2.507)	(0.880)
Dependent variable mean	79.28	59.55	48.05	61.76	14.02
Observations	8737818	8737825	8737897	8737905	8737918

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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 A16: Impact of pollution on health care expenditure by age, Wind IV model (entire sample)

	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					
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 A17: Impact of pollution on health care expenditure by age, Strike IV model (entire sample)

	Age 0 to 10	Age 11 to 20	Age 21 to 30	Age 31 to 40	Age 41 to 50
NO2 mean	1.578***	1.812***	0.410	2.179***	0.511
	(0.250)	(0.380)	(0.292)	(0.574)	(0.464)
Effect relative to mean (%)	6.24	5.86	3.00	5.02	1.12
O3 mean	1.402***	2.518***	-1.017***	1.562**	-0.0514
	(0.266)	(0.413)	(0.296)	(0.523)	(0.572)
Effect relative to mean (%)	5.5	8.1	-7.4	3.6	-0.1
Dependent variable mean	25.30	30.91	13.67	43.41	45.78
Observations	6539947	6539945	6539950	6539912	6539903
First-stage F-stat	3765.9	3767.3	3765.7	3765.9	3765.5
	51 to 60	Age 61 to 70	Age 71 to 80	Age 81 to 90	Over 90
NO2 mean	3.733***	3.817***	3.277***	1.191*	-0.0935
	(0.747)	(0.600)	(0.574)	(0.551)	(0.194)
Effect relative to mean (%)	4.70	6.41	6.82	1.93	-0.67
O3 mean	3.643***	1.539**	2.543***	0.745	0.761**
	(0.763)	(0.585)	(0.531)	(0.521)	(0.233)
Effect relative to mean (%)	4.6	2.6	5.3	1.2	5.4
Dependent variable mean	79.28	59.55	48.05	61.76	14.02
Observations	6539865	6539879	6539937	6539947	6539966
First-stage F-stat	3765.4	3765.8	3765.5	3765.3	3765.7

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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 A18: OLS and IV estimates of effect of NO2 and O3 on health care expenditure

	No chronic disease			Chronic disease		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	3.461***	1.612**	9.142***	4.296***	7.815***	7.249***
	(0.239)	(0.604)	(1.005)	(0.332)	(0.919)	(1.487)
Effect relative to mean (%)	1.61	0.75	4.25	1.79	3.25	3.02
O3 mean	0.392***	0.928**	9.694***	0.481***	3.799***	1.382
	(0.033)	(0.290)	(0.982)	(0.059)	(0.435)	(1.433)
Effect relative to mean (%)	0.18	0.43	4.51	0.20	1.58	0.58
Constant	27.99***			-155.5***		
	(6.157)			(16.724)		
Dependent variable mean	215.09	215.09	215.09	240.23	240.23	240.23
Observations	8472603	8484259	6539813	8472731	8484387	6539926
First-stage F-stat		8805.3	3765.8		8805.4	3765.4

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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 by department, month by year, and postcode fixed effects.

Table A19: OLS and IV estimates of effect of NO2 and O3 on health care expenditure

	No CMU			CMU		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	3.830***	4.097***	26.75***	0.359***	0.189	1.253***
	(0.328)	(1.126)	(1.795)	(0.045)	(0.219)	(0.327)
Effect relative to mean (%)	1.0	1.1	7.2	1.6	0.9	5.6
O3 mean	0.641***	1.830***	3.237*	0.0538***	0.0966	-0.0369
	(0.053)	(0.548)	(1.591)	(0.010)	(0.104)	(0.339)
Effect relative to mean (%)	0.2	0.5	0.9	0.2	0.4	-0.2
Constant	-295.7***			-24.12***		
	(20.085)			(2.873)		
Mean of dependent variable	372.35	372.35	372.35	22.23	22.23	22.23
Observations	8495959	8484337	6539879	8496034	8484412	6539943
First-stage F-stat		8804.9	3765.4		8805.7	3765.6

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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: OLS estimates of effect of NO2 and O3 on health care expenditure by medical specialty - entire sample

	Family med.	O.R.L.	Ophtalmo.	Stoma.	Chir. den.
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)
Constant	58.46***	-0.0172	2.391***	0.145	1.373
	(3.967)	(0.154)	(0.406)	(0.177)	(1.718)
Observations	8737859	8737946	8737944	8737950	8737935
	Cardio-vasc.	Pneumology	Neurology	Gyneco.	Chir. trauma
NO2 mean	0.140***	0.0339***	0.0393***	0.103***	0.0824***
	(0.012)	(0.006)	(0.006)	(0.010)	(0.009)
O3 mean	0.0113***	0.00261	0.00372*	0.00726***	0.00792***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Constant	-0.239	0.957***	1.361***	1.124***	-1.565***
	(0.384)	(0.265)	(0.252)	(0.273)	(0.353)
Observations	8737944	8737950	8737951	8737945	8737939
	Ambulance	Gastro. hep.	Rhuma.	Nephrology	Chir. plas.
NO2 mean	0.141***	0.0543***	0.0502***	0.0136***	0.0255***
	(0.016)	(0.016)	(0.006)	(0.003)	(0.005)
O3 mean	0.0267***	0.00636	0.00301	0.00247*	0.00362**
	(0.004)	(0.005)	(0.002)	(0.001)	(0.001)
Constant	-3.908***	-0.314	1.360***	0.509**	-0.493**
	(0.604)	(0.734)	(0.288)	(0.168)	(0.181)
Observations	8737936	8737950	8737951	8737951	8737952

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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 A21: OLS estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas

	Family med.	O.R.L.	Ophtalmo.	Stoma.	Chir. den.
NO2 mean	2.363***	0.0894***	0.274***	0.0518**	1.526***
	(0.306)	(0.014)	(0.044)	(0.019)	(0.188)
O3 mean	0.248*	0.00898	0.0316*	0.00927	0.179**
	(0.117)	(0.007)	(0.015)	(0.006)	(0.054)
Constant	243.0***	-0.274	8.825**	1.135	8.588
	(28.920)	(1.034)	(2.788)	(1.481)	(12.240)
Observations	874918	874923	874921	874925	874920
	Cardio-vasc.	Pneumology	Neurology	Gyneco.	Chir. trauma
NO2 mean	0.227***	0.0172	0.0705***	0.167***	0.117***
	(0.039)	(0.018)	(0.019)	(0.032)	(0.030)
O3 mean	0.0311*	0.00143	0.00393	0.0261*	0.00583
	(0.013)	(0.011)	(0.008)	(0.012)	(0.013)
Constant	-0.0741	3.849*	5.133***	5.840**	-6.222**
	(2.682)	(1.693)	(1.522)	(2.051)	(2.213)
Observations	874919	874926	874926	874925	874924
	Ambulance	Gastro. hep.	Rhuma.	Nephrology	Chir. plas.
NO2 mean	0.268***	0.00417	0.0483*	0.0192	0.0696***
	(0.051)	(0.060)	(0.020)	(0.012)	(0.021)
O3 mean	0.111***	0.0238	0.00331	0.0130	0.0182*
	(0.023)	(0.036)	(0.011)	(0.007)	(0.008)
Constant	-16.84***	-7.958	4.594**	1.663	-2.076
	(4.417)	(5.828)	(1.445)	(1.106)	(1.204)
Observations	874919	874924	874926	874925	874926

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A22: OLS estimates of effect of NO2 and O3 on health care expenditure by medical specialty - sample of the biggest 70 cities

	Family med.	O.R.L.	Ophtalmo.	Stoma.	Chir. den.
NO2 mean	2.877***	0.111***	0.529***	0.0977*	2.455***
	(0.606)	(0.031)	(0.083)	(0.047)	(0.371)
O3 mean	0.367	0.0169	0.0918*	0.0136	0.336*
	(0.238)	(0.019)	(0.037)	(0.013)	(0.132)
Constant	339.2***	-0.261	11.47	5.471	0.801
	(88.451)	(2.948)	(7.985)	(4.864)	(37.155)
Observations	236760	236759	236757	236759	236759
	Cardio-vasc.	Pneumology	Neurology	Gyneco.	Chir. trauma
NO2 mean	0.265**	-0.0207	0.109**	0.222**	0.107
	(0.085)	(0.040)	(0.040)	(0.073)	(0.066)
O3 mean	0.0599	0.0272	-0.00422	0.0381	-0.0117
	(0.033)	(0.026)	(0.018)	(0.033)	(0.026)
Constant	-2.941	5.193	10.69*	10.93	-6.028
	(7.803)	(3.897)	(4.309)	(5.998)	(6.136)
Observations	236753	236760	236760	236760	236758
	Ambulance	Gastro. hep.	Rhuma.	Nephrology	Chir. plas.
NO2 mean	0.401***	0.00657	0.0397	0.0217	0.110*
	(0.115)	(0.162)	(0.049)	(0.027)	(0.044)
O3 mean	0.196***	0.171	0.0277	0.0389*	0.0439*
	(0.058)	(0.114)	(0.029)	(0.019)	(0.022)
Constant	-30.26*	-23.81	6.016	0.845	-5.607
	(12.292)	(16.926)	(3.789)	(3.071)	(3.138)
Observations	236758	236759	236760	236759	236760

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A23: Impact of pollution on health care expenditure by medical specialty, OLS model - sample of the 10% most populated postcode areas, interaction of weekday fixed effects with postcode fixed effects

	Family medicine	O.R.L.	Ophthal-mology	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
	Gastro-hepatology	Rhuma-tology	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 A24: Impact of pollution on health care expenditure by medical specialty, OLS model - sample of the 70 biggest cities, interaction of weekday fixed effects with postcode fixed effects

	Family medicine	O.R.L.	Ophthal-mology	Stomatology	Dentistry
NO2 mean	3.330***	0.0729**	0.422***	0.0562	2.010***
	(0.480)	(0.027)	(0.076)	(0.044)	(0.302)
O3 mean	0.498*	0.0298	0.0438	0.0151	0.346*
	(0.205)	(0.017)	(0.040)	(0.015)	(0.139)
Observations	214905	214905	214902	214904	214904
	Cardio-vascular	Pneumology	Neurology	Gynecology	Ambulance
NO2 mean	0.170*	-0.00336	0.127**	0.191**	0.489***
	(0.080)	(0.042)	(0.045)	(0.067)	(0.117)
O3 mean	0.0724*	0.0329	0.00100	0.0172	0.186**
	(0.030)	(0.030)	(0.020)	(0.036)	(0.057)
Observations	214898	214905	214905	214905	214903
	Gastro-hepatology	Rhuma-tology	Nephrology	Trauma surgery	Plastic surgery
NO2 mean	0.0783	0.0595	-0.000550	0.0530	0.0961
	(0.193)	(0.049)	(0.033)	(0.067)	(0.050)
O3 mean	0.138	0.0247	0.0434*	-0.0180	0.0412
	(0.099)	(0.027)	(0.020)	(0.032)	(0.023)
Observations	214904	214905	214904	214903	214905

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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 A25: Strike IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - entire sample

	General med.	O.R.L.	Ophtalmo.	Stoma.	Chir. den.
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-vasc.	Pneumology	Neurology	Gyneco.	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
	Gastro. hep.	Rhuma.	Nephrology	Chir. trauma	Chir. plas.
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.

Table A26: Strike IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas

	General med.	O.R.L.	Ophtalmo.	Stoma.	Chir. den.
NO2 mean	17.25	1.094*	1.428	0.0979	22.26***
	(10.595)	(0.524)	(1.441)	(0.715)	(6.246)
O3 mean	12.01	0.759*	0.814	-0.0128	12.41***
	(7.142)	(0.330)	(0.925)	(0.442)	(3.715)
Observations	637449	637453	637451	637453	637453
First-stage F-stat	425.0	424.8	424.8	424.8	424.8
	Cardio-vasc.	Pneumology	Neurology	Gyneco.	Ambulance
NO2 mean	1.194	1.438	0.964	4.444***	-2.607
	(1.113)	(1.177)	(0.843)	(1.280)	(2.046)
O3 mean	1.224	1.203	0.503	1.918*	4.087**
	(0.819)	(0.701)	(0.579)	(0.750)	(1.473)
Observations	637454	637454	637454	637454	637449
First-stage F-stat	424.8	424.8	424.8	424.8	424.8
	Gastro. hep.	Rhuma.	Nephrology	Chir. trauma	Chir. plas.
NO2 mean	3.665	0.847	-0.882	3.165*	1.384
	(3.995)	(0.968)	(0.691)	(1.473)	(1.042)
O3 mean	0.212	0.742	-0.626	0.605	0.660
	(2.585)	(0.581)	(0.479)	(0.940)	(0.592)
Observations	637452	637454	637453	637452	637454
First-stage F-stat	424.8	424.8	424.8	424.8	424.8

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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.

Table A27: Strike IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas - sample of the biggest 70 cities

	General med.	O.R.L.	Ophtalmo.	Stoma.	Chir. den.
NO2 mean	26.66	2.548	2.940	-1.683	49.18**
	(22.030)	(1.324)	(3.301)	(1.738)	(15.064)
O3 mean	16.48	1.383	2.351	-1.018	25.47**
	(15.834)	(0.889)	(2.024)	(1.166)	(8.949)
Observations	162491	162491	162490	162490	162491
First-stage F-stat	162.3	162.3	162.3	162.3	162.3
	Cardio-vasc.	Pneumology	Neurology	Gyneco.	Ambulance
NO2 mean	0.430	3.011	-0.242	5.438*	-6.408
	(2.442)	(2.251)	(2.015)	(2.615)	(4.429)
O3 mean	1.166	2.429	-0.217	1.515	4.148
	(1.463)	(1.377)	(1.441)	(1.532)	(3.164)
Observations	162491	162491	162491	162491	162489
First-stage F-stat	162.3	162.3	162.3	162.3	162.3
	Gastro. hep.	Rhuma.	Nephrology	Chir. trauma	Chir. plas.
NO2 mean	10.17	2.857	-0.439	3.905	1.376
	(9.961)	(2.496)	(1.591)	(3.287)	(2.000)
O3 mean	2.460	2.220	-0.662	0.810	0.0277
	(6.360)	(1.491)	(1.073)	(2.290)	(1.157)
Observations	162490	162491	162490	162489	162491
First-stage F-stat	162.3	162.3	162.3	162.3	162.3

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A28: Impact of pollution on health care expenditure by medical specialty, strike IV model - sample of the 10% most populated postcode areas, interaction of weekday fixed effects with postcode fixed effects

	Family medicine	O.R.L.	Ophthal-mology	Stomatology	Dentistry
NO2 mean	16.83***	0.184	1.263**	0.101	6.412**
	(2.828)	(0.179)	(0.478)	(0.218)	(2.061)
O3 mean	8.354*	0.489	2.140**	-0.0466	8.454***
	(4.001)	(0.250)	(0.658)	(0.292)	(2.557)
Observations	637449	637453	637451	637453	637453
First-stage F-stat	492.0	491.8	491.8	491.8	491.8
	Cardio-vascular	Pneumology	Neurology	Gynecology	Ambulance
NO2 mean	0.0686	0.296	0.568*	1.399***	-0.480
	(0.379)	(0.412)	(0.283)	(0.374)	(0.680)
O3 mean	0.870	1.016*	1.033*	0.705	0.365
	(0.593)	(0.435)	(0.406)	(0.411)	(0.834)
Observations	637454	637454	637454	637454	637449
First-stage F-stat	491.8	491.8	491.8	491.8	491.8
	Gastro-hepatology	Rhuma-tology	Nephrology	Trauma surgery	Plastic surgery
NO2 mean	2.851*	0.340	0.0653	1.756***	0.450
	(1.153)	(0.299)	(0.207)	(0.479)	(0.305)
O3 mean	0.325	0.966*	-0.0351	0.899	0.0786
	(1.582)	(0.408)	(0.269)	(0.615)	(0.286)
Observations	637452	637454	637453	637452	637454
First-stage F-stat	491.8	491.8	491.8	491.8	491.8

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

Table A29: Impact of pollution on health care expenditure by medical specialty, strike IV model - sample of the 70 biggest cities, interaction of weekday fixed effects with postcode fixed effects

	Family medicine	O.R.L.	Ophthal-mology	Stomatology	Dentistry
NO2 mean	31.94*	1.371	3.303	-1.513	34.59**
	(14.790)	(0.973)	(2.401)	(1.349)	(10.886)
O3 mean	21.44	0.907	3.232	-1.007	20.48**
	(12.236)	(0.795)	(1.784)	(1.038)	(7.560)
Observations	162491	162491	162490	162490	162491
First-stage F-stat	217.7	217.7	217.7	217.7	217.7

	Cardio-vascular	Pneumology	Neurology	Gynecology	Ambulance
NO2 mean	0.00835	3.079	0.251	3.912*	-4.865
	(1.759)	(1.682)	(1.517)	(1.844)	(3.214)
O3 mean	1.028	2.704*	0.122	1.122	4.685
	(1.298)	(1.280)	(1.294)	(1.248)	(2.847)
Observations	162491	162491	162491	162491	162489
First-stage F-stat	217.7	217.7	217.7	217.7	217.7

	Gastro-hepatology	Rhuma-tology	Nephrology	Trauma surgery	Plastic surgery
NO2 mean	7.933	2.869	-0.545	2.958	0.684
	(7.101)	(1.791)	(1.172)	(2.389)	(1.343)
O3 mean	2.195	2.481*	-0.740	0.662	-0.299
	(5.373)	(1.260)	(0.925)	(1.965)	(0.948)
Observations	162490	162491	162490	162489	162491
First-stage F-stat	217.7	217.7	217.7	217.7	217.7

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

Table A30: Wind IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - entire sample

	General med.	O.R.L.	Ophtalmo.	Stoma.	Chir. den.
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-vasc.	Pneumology	Neurology	Gyneco.	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
	Gastro. hep.	Rhuma.	Nephrology	Chir. trauma	Chir. plas.
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 A31: Wind IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas

	General med.	O.R.L.	Ophtalmo.	Stoma.	Chir. den.
NO2 mean	4.275**	-0.0571	0.0564	-0.00259	0.0470
	(1.307)	(0.087)	(0.213)	(0.097)	(0.786)
O3 mean	3.578***	-0.0327	0.0661	0.0102	-0.0568
	(0.864)	(0.057)	(0.140)	(0.064)	(0.508)
Observations	836729	836735	836732	836736	836731
First-stage F-stat	1355.9	1355.9	1356.0	1355.9	1355.9
	Cardio-vasc.	Pneumology	Neurology	Gyneco.	Ambulance
NO2 mean	0.151	-0.200	0.322*	0.170	2.443***
	(0.166)	(0.227)	(0.147)	(0.143)	(0.366)
O3 mean	0.109	-0.108	0.212*	0.148	1.639***
	(0.113)	(0.144)	(0.095)	(0.098)	(0.239)
Observations	836730	836737	836737	836736	836730
First-stage F-stat	1355.8	1355.9	1355.9	1355.9	1355.9
	Gastro. hep.	Rhuma.	Nephrology	Chir. trauma	Chir. plas.
NO2 mean	0.640	-0.0824	0.104	0.118	-0.0750
	(0.609)	(0.135)	(0.084)	(0.191)	(0.111)
O3 mean	0.368	-0.0316	0.0765	0.0737	-0.0841
	(0.396)	(0.088)	(0.054)	(0.130)	(0.075)
Observations	836735	836737	836736	836735	836737
First-stage F-stat	1355.9	1355.9	1355.9	1355.9	1355.9

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A32: Wind IV estimates of effect of NO2 and O3 on health care expenditure by medical specialty - 10% most populated postcode areas - sample of the biggest 70 cities

	General med.	O.R.L.	Ophtalmo.	Stoma.	Chir. den.
NO2 mean	3.905	-0.213	-0.101	0.139	-0.272
	(2.634)	(0.203)	(0.489)	(0.242)	(1.734)
O3 mean	3.794	-0.122	-0.139	0.137	-0.585
	(2.021)	(0.159)	(0.381)	(0.187)	(1.328)
Observations	215203	215203	215200	215202	215202
First-stage F-stat	551.1	551.1	551.0	551.0	551.1

	Cardio-vasc.	Pneumology	Neurology	Gyneco.	Ambulance
NO2 mean	0.0397	-0.520	0.997**	0.730*	3.747***
	(0.370)	(0.511)	(0.351)	(0.318)	(0.878)
O3 mean	0.0367	-0.389	0.743**	0.612*	2.948***
	(0.301)	(0.406)	(0.265)	(0.263)	(0.649)
Observations	215196	215203	215203	215203	215201
First-stage F-stat	551.0	551.1	551.1	551.1	551.2

	Gastro. hep.	Rhuma.	Nephrology	Chir. trauma	Chir. plas.
NO2 mean	0.927	-0.588*	0.100	-0.182	-0.328
	(1.482)	(0.298)	(0.189)	(0.424)	(0.238)
O3 mean	0.613	-0.379	0.108	-0.108	-0.262
	(1.177)	(0.223)	(0.140)	(0.361)	(0.190)
Observations	215202	215203	215202	215201	215203
First-stage F-stat	551.1	551.1	551.1	551.1	551.1

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

Table A33: Impact of pollution on health care expenditure by medical specialty, wind IV model - sample of the 10% most populated postcode areas, interaction of weekday fixed effects with postcode fixed effects

	Family medicine	O.R.L.	Ophthal-mology	Stomatology	Dentistry
NO2 mean	6.177*	0.147	0.319	0.250	2.742
	(2.699)	(0.153)	(0.441)	(0.211)	(1.540)
O3 mean	7.267**	0.179	0.382	0.270	3.080*
	(2.477)	(0.139)	(0.400)	(0.193)	(1.387)
Observations	836729	836735	836732	836736	836731
First-stage F-stat	1243.1	1243.1	1243.1	1243.1	1243.0
	Cardio-vascular	Pneumology	Neurology	Gynecology	Ambulance
NO2 mean	0.395	-0.459	0.488	0.418	3.647***
	(0.346)	(0.500)	(0.311)	(0.312)	(0.706)
O3 mean	0.458	-0.413	0.405	0.465	3.378***
	(0.321)	(0.444)	(0.279)	(0.285)	(0.652)
Observations	836730	836737	836737	836736	836730
First-stage F-stat	1243.0	1243.1	1243.1	1243.1	1243.1
	Gastro-hepatology	Rhuma-tology	Nephrology	Trauma surgery	Plastic surgery
NO2 mean	1.094	-0.0973	-0.111	0.520	-0.357
	(1.299)	(0.292)	(0.164)	(0.414)	(0.246)
O3 mean	0.941	-0.0504	-0.102	0.526	-0.361
	(1.172)	(0.263)	(0.148)	(0.382)	(0.228)
Observations	836735	836737	836736	836735	836737
First-stage F-stat	1243.1	1243.1	1243.2	1243.1	1243.1

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

Table A34: Impact of pollution on health care expenditure by medical specialty, wind IV model - sample of the 70 biggest cities, interaction of weekday fixed effects with postcode fixed effects

	Family medicine	O.R.L.	Ophthal-mology	Stomatology	Dentistry
NO2 mean	1.746	-0.212	-0.176	0.146	-0.276
	(2.366)	(0.195)	(0.475)	(0.243)	(1.684)
O3 mean	2.270	-0.104	-0.153	0.148	-0.433
	(1.818)	(0.152)	(0.371)	(0.189)	(1.285)
Observations	215203	215203	215200	215202	215202
First-stage F-stat	546.6	546.6	546.5	546.5	546.6

	Cardio-vascular	Pneumology	Neurology	Gynecology	Ambulance
NO2 mean	0.0848	-0.564	0.919**	0.644*	3.708***
	(0.354)	(0.514)	(0.347)	(0.298)	(0.873)
O3 mean	0.0998	-0.428	0.688**	0.559*	2.976***
	(0.288)	(0.412)	(0.263)	(0.246)	(0.655)
Observations	215196	215203	215203	215203	215201
First-stage F-stat	546.5	546.6	546.6	546.6	546.6

	Gastro-hepatology	Rhuma-tology	Nephrology	Trauma surgery	Plastic surgery
NO2 mean	0.860	-0.612*	0.0910	-0.175	-0.322
	(1.422)	(0.292)	(0.185)	(0.421)	(0.239)
O3 mean	0.568	-0.394	0.108	-0.0876	-0.256
	(1.139)	(0.218)	(0.137)	(0.358)	(0.190)
Observations	215202	215203	215202	215201	215203
First-stage F-stat	546.6	546.6	546.6	546.5	546.6

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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 A35: OLS and IV estimates of effect of NO2 and O3 on health care expenditure - simpler fixed effect structure

	Total spending - entire France			Total spending - 70 biggest cities		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	5.784***	7.566***	21.68***	16.52***	24.74*	113.6***
	(0.380)	(1.240)	(2.061)	(2.588)	(9.964)	(22.742)
O3 mean	0.894***	3.942***	19.68***	5.798***	23.51**	76.79**
	(0.059)	(0.591)	(1.947)	(0.847)	(8.007)	(26.583)
Constant	71.34***			659.3*		
	(16.501)			(312.327)		
Observations	8495951	8484329	6539870	215497	215203	162491
First-stage F-stat		8805.0	3765.3		575.4	171.4

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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 A36: OLS and IV estimates of effect of NO2 and O3 on health care expenditure - simpler time fixed effect structure, excluding also day of week fixed effecst

	Total spending - entire France			Total spending - 70 biggest cities		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	17.35***	24.82***	30.96***	69.19***	73.06***	294.5***
	(0.586)	(1.296)	(3.179)	(6.609)	(11.286)	(35.406)
O3 mean	1.800***	12.25***	123.7***	9.684***	61.16***	486.8***
	(0.073)	(0.631)	(5.622)	(1.154)	(9.190)	(67.012)
Constant	85.52***			856.4**		
	(15.125)			(288.059)		
Observations	8495951	8484329	6539870	215497	215203	162491
First-stage F-stat		8259.5	3665.6		581.4	252.9

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

Table A37: OLS and IV estimates of effect of NO2 and O3 on health care expenditure - no weather controls

	Total spending - entire France			Total spending - 70 biggest cities		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	4.172***	11.92***	14.76***	10.90***	36.35**	143.7**
	(0.300)	(2.058)	(2.655)	(1.893)	(13.423)	(54.796)
O3 mean	0.438***	7.710***	20.22***	2.925***	36.71**	124.7**
	(0.039)	(1.246)	(1.899)	(0.552)	(12.452)	(38.515)
Constant	-2.612			123.5		
	(16.075)			(315.979)		
Observations	8761843	8484329	6743844	237412	215203	178993
First-stage F-stat		9163.6	2665.8		654.1	90.17

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

Table A38: OLS and IV estimates of effect of NO2 and O3 on health care expenditure - no weather controls and simple fixed effect structure

	Total spending - entire France			Total spending - 70 biggest cities		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	4.185***	11.92***	14.76***	12.17***	39.09*	133.8***
	(0.286)	(2.058)	(2.655)	(1.988)	(15.892)	(25.661)
O3 mean	0.494***	7.710***	20.22***	3.478***	41.47**	85.04**
	(0.038)	(1.246)	(1.899)	(0.589)	(15.233)	(26.226)
Constant	128.4***			1026.7***		
	(13.017)			(235.598)		
Observations	8761843	8484329	6743844	237412	215203	178993
First-stage F-stat		9163.6	2665.8		678.1	148.0

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

Table A39: OLS and IV estimates of effect NO2 and O3 on health care expenditure, inclusion of pollution and weather lags

	Total spending - entire France			Total spending - 70 biggest cities		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	7.230***	29.81***	40.73***	16.17***	66.31**	120.8*
	(0.498)	(2.745)	(4.115)	(2.756)	(21.956)	(51.479)
O3 mean	0.866***	15.76***	15.19***	4.840***	60.83**	167.3**
	(0.072)	(1.464)	(3.620)	(0.839)	(19.753)	(52.772)
Constant	24.30			-27.59		
	(15.364)			(400.410)		
Observations	8472673	8472673	6518056	214905	214905	161943
First-stage F-stat		7364.7	1768.0		576.7	111.2

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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.

Table A40: IV estimates of effect of log NO2 and log O3 on log health care expenditure, different strike IV specifications

	Total spent[a]	Total spent[b]	Total spent[c]	Total spent[d]	Total spent[e]
NO2 mean	38.79***	19.42***			20.09***
	(3.296)	(2.022)			(2.312)
O3 mean			39.29***	17.27***	22.31***
			(3.757)	(1.944)	(2.492)
PM 10 mean					6.000
					(3.697)
Observations	6539870	6539870	6539870	6539870	6539870
First-stage F-stat	2756.9	3765.3	484.3	1515.7	3765.3

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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.

[a] - NO2 pollution instrumented by a dummy equal to 1 when a strike takes place the first, second or third day, and 0 otherwise.

[b] - NO2 pollution instrumented by three dummies equal to 1 when a strike takes place the first day, second or third day, respectively and 0 otherwise.

[c] - O3 pollution instrumented by a dummy equal to 1 when a strike takes place the first, second or third day, and 0 otherwise.

[d] - O3 pollution instrumented by three dummies equal to 1 when a strike takes place the first day, second or third day, respectively and 0 otherwise.

[e] - NO2, O3 and PM pollution simultaneously instrumented by three dummies equal to 1 when a strike takes place the first day, second or third day, respectively and 0 otherwise.

Table A41: IV estimates of effect of log NO2 and log O3 on log health care expenditure, different wind IV specifications

	Total spent[a]	Total spent[b]	Total spent[c]	Total spent[d]
NO2 mean	-0.348	-0.794***		
	(0.192)	(0.190)		
O3 mean			0.173	0.436***
			(0.096)	(0.090)
Observations	8495951	8484329	8495951	8484329
First-stage F-stat	21289.0	8805.0	73950.1	27595.0

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. 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 pollution instrumented by a dummy equal to 1 when wind is below average on day t.
[b] - NO2 pollution instrumented by three dummies equal to 1 when wind is below average on day t, t-1, and t-2 respectively and 0 otherwise.
[c] - O3 pollution instrumented by a dummy equal to 1 when wind is below average on day t.
[d] - O3 pollution instrumented by three dummies equal to 1 when wind is below average on day t, t-1, and t-2 respectively and 0 otherwise.

Table A42: OLS and IV estimates of effect NO2 and O3 on health care expenditure - controlling for PM10 and PM2.5

	Total spending - PM10 control			Total spending - PM2.5 control		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	6.542***	7.409***	20.72***	6.725***	7.589***	21.32***
	(0.455)	(0.941)	(2.277)	(0.460)	(1.056)	(2.013)
O3 mean	0.799***	3.735***	21.00***	0.688***	3.845***	22.35***
	(0.057)	(0.394)	(2.346)	(0.051)	(0.459)	(2.469)
PM 10 mean	-1.298***	-0.363	1.907			
	(0.124)	(0.218)	(1.511)			
PM 2.5 mean				-2.071***	-0.307	6.059**
				(0.165)	(0.202)	(1.964)
Constant	-47.40*			-45.73*		
	(18.741)			(18.691)		
Observations	8495951	8484329	6539870	8490140	8478518	6534790
First-stage F-stat		9716.0	3824.1		7321.4	5085.0

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. 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 A43: IV estimates of effect PM10 or PM2.5 and O3 on health care expenditure, controlling for NO2

	Tot. spending - PM10 and O3		Tot. spending - PM2.5 and O3	
	Wind IV	Strike IV	Wind IV	Strike IV
	(1)	(2)	(3)	(4)
PM 10 mean	1.226*	5.790		
	(0.609)	(3.680)		
PM 2.5 mean			1.495	7.729*
			(0.837)	(3.620)
O3 mean	5.783***	19.23***	5.880***	20.54***
	(0.396)	(2.028)	(0.427)	(2.219)
NO2 mean	10.59***	22.77***	10.64***	23.58***
	(0.680)	(1.917)	(0.686)	(1.655)
Constant	151.2			
	(351.979)			
Observations	8484329	6539870	162491	6534790
First-stage F-stat	12978.7	2717.5	20.78	3768.2

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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, year, and postcode fixed effects.

Table A44: OLS and IV estimates of effect of log NO2 and log O3 on log health care expenditure

	Total spending - entire France, OLS regressions			
NO2 mean	4.677***			
	(0.326)			
O3 mean		-0.248***		
		(0.034)		
PM 10 mean			0.875***	
			(0.080)	
PM 2.5 mean				0.408***
				(0.069)
Constant	14.66	84.97***	52.30***	63.09***
	(15.167)	(11.561)	(13.099)	(12.595)
Observations	8495951	8495951	8495951	8490140
	Total spending - entire France, Wind IV regressions			
NO2 mean	-0.794***			
	(0.190)			
O3 mean		0.436***		
		(0.090)		
PM 10 mean			-1.487***	
			(0.244)	
PM 2.5 mean				-1.509***
				(0.259)
Observations	8484329	8484329	8484329	8478518
First-stage F-stat	8805.0	27595.0	6953.4	9292.5
	Total spending - entire France, Strike IV regressions			
NO2 mean	19.42***			
	(2.022)			
O3 mean		17.27***		
		(1.944)		
PM 10 mean			-2.832	
			(2.629)	
PM 2.5 mean				-15.97***
				(2.837)
Observations	6539870	6539870	6539870	6534790
First-stage F-stat	3765.3	1515.7	3126.4	3220.1

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$. 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, year, and postcode fixed effects.

Table A45: OLS and IV estimates of effect of NO2 and log O3 on health insurance reimbursements for sick leave

	Sick leave spending - entire France			Sick leave spending - 70 biggest cities		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	0.00835*	0.147*	0.118	-0.0264	-0.267	-2.190
	(0.004)	(0.065)	(0.105)	(0.033)	(0.220)	(1.635)
O3 mean	0.00530**	0.0761*	-0.412***	-0.00279	-0.152	-1.268
	(0.002)	(0.031)	(0.089)	(0.014)	(0.173)	(1.000)
Constant	1.205***			6.032*		
	(0.251)			(2.608)		
Observations	8496076	8484454	6539974	215497	215203	162491
First-stage F-stat		8805.3	3765.8		551.1	162.3

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A46: OLS and IV estimates of effect of NO2 and log O3 on number of deaths

	Number of deaths - entire France			Number of deaths - 70 biggest cities		
	OLS	Wind IV	Strike IV	OLS	Wind IV	Strike IV
	(1)	(2)	(3)	(4)	(5)	(6)
NO2 mean	0.0000130**	-0.0000819	-0.000157	0.0000626	-0.000375	0.00136
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
O3 mean	0.00000327*	-0.0000419	-0.000209*	0.0000103	-0.000286	0.00150
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Constant	0.00239***			0.0121**		
	(0.000)			(0.004)		
Observations	8496076	8484454	6539974	215497	215203	162491
First-stage F-stat		8805.3	3765.8		551.1	162.3

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. 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 A47: Wind direction IV and thermal inversion IV estimates of effect of log NO2 and log O3 on health care expenditure

	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.