Morbidity And Sulfur Dioxide: Evidence From French Strikes At Oil Refineries

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Abstract

This paper examines the impact of sulfur dioxide (SO_2) in France on health outcomes at a census track level. To do so, we use recent strikes affecting oil refineries in France, in October 2010, as a natural experiment. Our work offers several contributions. We first show that a temporal shut down in the refining process leads to a reduction in sulfur dioxide concentration. We then use this narrow time frame exogenous shock to assess the impact of a change in air pollution concentration on respiratory outcomes. Our estimates suggest that daily variation in SO_2 air pollution has economically significant health effects at levels below the current standard.

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1 Introduction

The issues of chronic exposure of the population to air emissions and the generated health hazards are increasingly the focus of debate. In June 2010, the US Environmental Protection Agency (EPA) strengthened the National Ambient Air Quality Standard for sulfur dioxide (SO_2). In august 2011, EPA is proposing to establish an additional set of secondary standards. The new 1-hour standard applies only to the primary standard set to protect public health. EPA is also currently working on a new, multi-pollutant standard which would provide the appropriate degree of protection. In the light of EPA, we may wonder if the EU should also revise the limit values for sulfur dioxide (SO2) for the protection of human health [1]. Health effects are now known to be associated with much lower levels of SO_2 than previously believed (World Health Organization (WHO), 2011). Because of remaining complexities and uncertainties, assessing the benefits and cost of lowering the standard is not an easy task. Accurate estimates that link contemporaneous air pollution exposure to observable health outcomes are needed (Schlenker and Walker, 2011).

Our study combines pollution concentration measures for sulfur dioxide (SO_2) with contemporaneous measure of morbidity, weather and socioeconomic data at a census tract level in France. We examine the effect of a daily change in pollution concentration measure on the number of respiratory hospital admissions. The main concern when estimating this effect is that there may be potential factors that affect both health outcomes and pollution. Individuals who live in areas of high pollution may be in worse health for reasons unrelated to pollution. Besides, pollution is rarely randomly assigned across individuals: preferences for health or air quality across individuals are heterogeneous and people may decide to live far from hazardous sites. To overcome these problems of unobserved covariates, we exploit exogenous variation in pollution due to strikes at oil refineries in France, in October 2010 [2]. Striking workers were blocking fuel supplies for about 30 days amid nationwide protests over pension reform and concern about the industry in France.

[1] In the air quality directive (2008/EC/50) the EU has set two limit values for sulphur dioxide (SO2) for the protection of human health: the SO2 hourly mean value may not exceed 350 micrograms per cubic metre (ţg/m3) more than 24 times in a year and the SO2 daily mean value may not exceed 125 micrograms per cubic metre (ţg/m3) more than 3 times in a year. In US, EPA sets its Primary standards to provide public health protection, including protecting the health of sensitive populations such as asthmatics, children, and the elderly at 75 parts per billion. The final rule was signed June 2, 2010.

[2] We focus on refineries for several reasons. First, the SO_2 emission from fuel combustion may be responsible for respiratory disease and lungs problems. SOx can react with other compounds in the atmosphere to form small particles. These particles penetrate deeply into sensitive parts of the lungs and can cause or worsen respiratory disease, such as emphysema and bronchitis (Environmental Protection Agency (EPA), 2011). Second, the importance given to oil refinery activity is ubiquitous. Strikes induce road fuel shortages making the overall economic activity dependent of oil supply. Third, refineries have important local effects. In contrast to transport emission, pollution from refineries is fixed and people living next to refineries may be further impacted by SO_2 release.

We aim to use this temporal event that caused sharp differential changes in air pollution across sites to identify the effects of air pollution on population morbidity. This research design is part of the recent literature about health and pollution dealing with non random selection and behavioral responses to pollution exposure that may bias previous estimation results. Schlenker and Walker exploit exogenous changes in daily airport traffic congestion in California to look at the relationship between airport congestion and local pollution levels (Schlenker and Walker, 2011). They find that one standard deviation change in congestion at Los Angeles International airport increases pollution levels of carbon monoxide (CO) by 19 percent of the day-to-day variance at a distance of 5 km from the airport. Chay and Greenstone use the 1981-82 recession to estimate the relationship between infant mortality and particulates air pollution (Chay and Greenstone, 2003). A 1 mg/m3 reduction in particulates results in about 4-8 fewer infant deaths per 100,000. The natural experiment employed by Frankenberg et al. use the forest fires in the Indonesian islands of Kalimantan and Sumatra in 1997. They first show that adults living in areas affected by the smoke were in worse health in 1997 than the ones living in other areas. They take this into account to finally compare changes in health for individuals in areas affected by smoke with changes for individuals outside the smoke areas and find that the fires had a significant deleterious impact on the health of Indonesian adults (Frankenberg et al., 2005). Beatty and Shimshack estimate the causal effect of air pollution on health outcome by looking at the school bus emissions programs. School bus retrofits induced statistically and economically significant reductions in bronchitis, asthma, pleurisy, and pneumonia incidence for sensitive populations (Beatty and Shimshack, 2011).

We make several contributions to the existing literature: We first shed light on the externality issue from oil refining. We show how a negative shock on economic production such strikes leads to a reduction in ambient air pollution. Second, this paper develops a novel approach to estimating the contemporaneous effect of pollution on health. We use French strikes at oil refinery as a natural experiment. Using fixed effects strategy, we exploit the reduction in SO_2 to understand how pollution levels affect health outcomes. Particularly, we compare the change for individual who live in geographical area located near the refinery with those who live in neighborhoods far from the refinery. Third, we use a rich and large dataset focusing on both respiratory distress and inpatient hospital discharge records. Not only we rely on patients staying at least one night in the hospital but we also consider the ones being admitted as an emergency [3]. Fourth, the narrow time frame of nearby 17 days allows us to assess the temporal effect of a reduction in air pollution on health. The treatment group should be statistically identical before and after the period of strikes, on both observed and unobserved characteristics, at baseline. Any change in characteristics

[3] Schlenker and Walker are the first one to focus on this contemporaneaous measure of health (Schlenker and Walker, 2011).

during strikes is due, therefore, to the strikes alone. Our baseline model relaxes the assumption we find in the previous literature saying that the relationship between pollution and health is the same for everyone in the population (Schlenker and Walker, 2011) (Hanna and Oliva, 2011) (Beatty and Shimshack, 2011). Even if people are heterogeneous and may sort themselves into locations with respect to pollution, it seems reasonable to consider a time frame of 15 days not long enough to observe such changes. Fifth, our paper looks at short-run health impacts on morbidity, especially respiratory admissions with respect to the international disease classification. [4]. Most previous studies, on a similar topic, look at the impact on mortality rate (Currie and Neidell, 2004) (Chay and Greenstone, 2003). However short-term pollution exposure may lead more likely to morbidity outcomes than mortality. Fifth, we look at acute localized effect of air pollution. Beatty and Shimshack emphasize that widely dispersed ambient air quality monitors, studied in the previous literature on this topic, hide large differences in localized pollution levels (Beatty and Shimshack, 2011).

Our findings have policy implications. First, the law requires EPA to periodically review the standards to ensure that they provide adequate health protection. In addition, European standard are lower than US standard. Our estimates suggest that daily variation in SO_2 air pollution has economically significant health effects at levels below European and US current standard. Regulation about SO_2 should certainly be strenghened. Secondly, we may also consider strengthening regulation about air pollution coming from refineries. Over the past 20 years, regulations concerning emissions from industrial activities and combustion plants have led to a dramatic reduction in atmospheric emissions of a large number of pollutants, including sulfur dioxide (SO_2). In France, Since the 1980s, SO_2 emissions have dropped by 85 percent (French Environment and Energy Management Agency (ADEME), 2012). However, since air pollution has not been eliminated, we may wonder to which extent a reduction in air pollution will be beneficial. The 218 European refineries are indeed responsible for 0.3 million tones of SO_2, that is 2 percent of the European total large point sources (LPS) emission (European Environmental Agency (EEA), 2011). In addition, the Ministry for Ecology, sustainable development and spatial planning (ADEME) via SEVESO sites [5] gives special attention to the monitoring of SO_2 from refineries, for which population information and alert procedures have been in place for several years, in light of the increasing expectations of local residents. Population information and alert procedures are regularly updated according to the evolution in regulatory requirements. Our study suggests that people located near refineries may be more exposed to pollution and might be

[4]Pollution peaks may induce asthma attacks or respiratory problems. Pollution has also long-run health impact. However, the nature of our dataset unable us to look at long-run effects

[5]SEVESO directive required that member States and companies identify the risks associated with certain hazardous industrial activities and take the necessary measures to deal with them. The Ministry for Ecology, sustainable development and spatial planning (ADEME) has developed a website listing the facilities concerned by the so-called SEVESO II Directive.

more adversely health affected to pollution than individual living far away from refineries. Abating pollution where impacted population lives and works may return larger benefits than costs. Third, implementation of public policy for the environment and energy management domains covered by ADEME requires greater socioeconomic expertise. People living near refineries may also be the one with low revenue (Viel et al., 2011) and this can imply more serious health risks. To promote environmental justice, localized pollution policies may be especially effective at the margin. Abating pollution where poorer population lives and works may return larger benefits than costs.

The rest of the paper is laid out as follows: We provide a background on the refinery closure and the impact of SO_2 on health. We then discuss data we compiled for the paper. In addition, we provide an overview of the economic implications of refinery emissions. In section 5, we describe the empirical strategy. Finally, we present the results in the last section .

2 Background: Refineries, Air pollution and Health

2.1 SO_2 pollution and the refinery closure

Refineries are responsible for 20 percent of SO_2 release in France (Soleille, 2004). Oil refineries convert crude oil to everyday product like gasoline, kerosene, liquefied petroleum. Crude oil and coal contain relatively high quantity of sulfur. Sulfur dioxide (SO_2) is creating when crude oil or coal is heated at the refinery to produce fuel. Thus, the refining process releases a large number of chemicals such as benzene, chromium and sulfur acid into the atmosphere. Refineries are considered upper tier SEVESO sites for most of their activities [6]. Imposing an appropriate ceiling to refineries in term of pollution release remains complex. In case of an accident such as in June 2011 with Feyzin Refinery [7], it remains difficult to know if ceilings have been overcome and to what extent population has been impacted.

France has 11 refineries and treats 89 million tones of petrol every year. The main 4 refining companies operating in France are Total, Shell, Esso and Ineos. The regions concerned are Haute Normandie, Provence Alpes Côtes d´Azur, Rhône-Alpes, Nord-Pas-de-Calais, Pays-de-la-Loire, Ile de France and Alsace. Total refineries are allowed to emit up to 3 500 tons of sulfur dioxide per year which corresponds to 9,6 tons a day. French refinery workers blocked production in October 2010 due to protests over pension reform and concern

[6] This category corresponds with the upper tier of the SEVESO II Directive. Both, Part 1 and Part 2 of Annex I, contain lower threshold quantities (lower tier): application of Art. 6 and 7 and upper threshold quantities (upper tier): application of Art. 6 and 9. (French Environment and Energy Management Agency (ADEME) , 2012)

[7] A leakage of Sulfur Dioxide occurred in a refinery near to the small town of Feyzin in June 2011.

about the industry in France. The French union for petrol industry (Ufip) has evaluated the striking cost at 230 Millions of Euros for the entire petrol industry (The French Union for Petrol Industry (UFIP), 2010). Strikes really started at the beginning of September but the first refinery started to close the 12th of October. As a consequence, production has been reduced at a minimum or has been shutted down nearby 15 days. Not surprisingly, figure 1 shows that locations that neighbored the areas where the refineries shutted down also experienced air quality improvements. On the other hand, census districts that did not have refineries and did not neighbor such census districts experienced minimal pollution changes. I consider Donges, Feyzin, Gonfreville l'Orcher and Petite Couronne because those refineries shutted down totally in October 2010; the rest of refineries were producing at a minimum and Notre Dame de Gravenchon refinery was not affected at all by strikes. Gonfreville l'Orcher and Donges are the two most significant refineries in France from Total company. Their refining capacity is up to 15,9 Millions of tonss and 11,3 Millions of tons a year, respectively. They have closed the 12th of October 2010 and have started again the 30th of October. Closing a refinery is a complex process which requires from 2 days to one week according the the size of the refinery. It takes as long to open it again. Thus, we may consider the impact and the reduction of SO_2 being stronger between mid October and the beginning of November .

2.2 SO_2 pollution and health

This paper focuses on sulfur dioxide (SO_2), one of the major pollutant emitted by oil refineries and the main pollutant from industrial pollution. Sulfur dioxide (SO_2) is one of a group of highly reactive gasses known as oxides of sulfur SO_x. The largest sources of SO_2 emissions are from fossil fuel combustion at power plants and other industrial facilities (Environmental Protection Agency (EPA), 2011). SO_2 is a colorless gas with a very strong smell. In France, the threshold for SO_2, fixed by the European act 2002-13 related to air quality, is 350 μg/m_3 in hourly average to protect human health. This ceiling should not be overcome more than 24 times a year. In comparison, since June 2010, The Clean Air Act has recquired EPA to set the one-hour SO_2 health standard at 75 parts per billion (ppb)[8]. Setting pollution threshold is particularly relevant since pollution concentration at a certain level has a delerious impact on health.

Subjects exposed to SO_2 showed decreased lung functioning for children and increased respiratory symptoms for adults (World Health Organization (WHO), 2011), asthma crisis and ocular rash (Pierre Lecoq, 2009). Inflammation of the respiratory tract causes coughing, mucus secretion, aggravation of asthma and chronic bronchitis and makes people more prone

[8] ppb is a volume of gaseous pollutant by 10^9 volumes of ambient air. μg/m_3 is micrograms of gaseous pollutant per cubic meter of ambient air with 1 ppb = 2.66 μg/m_3 for SO_2

to infections of the respiratory tract (World Health Organization (WHO), 2011). The effects seem stronger for high levels of exposure and people with asthma are more sensitive to SO_2. The number of hospital admission for cardiopathy and mortality increases on days with high SO2 air concentration (Finkelstein et al., 2003). Human clinical studies consistently demonstrate respiratory morbidity among exercising asthmatics following peak exposures (5-10 min) to SO_2 concentrations equals 0.4 ppm, with respiratory effects occurring at concentrations as low as 0.2 ppm in some asthmatics (World Health Organization (WHO), 2005).

3 Economic implications

3.1 The impact of pollution on labor and consumption

Moderate effects of pollution on health may exert an important influence on labor market decisions. Literature sheds light on the presumption that air pollution and environmental conditions is likely to impair workers ability to perform their job. An improvement in air quality can substantially increase the amount of hours worked. In other words, if pollution damage the health of an individual or his or her dependents, individuals may be more likely to miss work because either they or their children are home sick (Hanna and Oliva, 2011). In this context, Croker and Robert find that ozone air pollution prevalent in southern california does reduce daily earnings for citrus harvesting (Crocker and Horst, 1981). Neidell and Graff Zivin provide robust evidence that ozone levels well below federal air quality standards have a significant impact on productivity (Zivin and Neidell, 2011). They claim environmental protection can also be viewed as an investment in human capital, and its contribution to firm productivity and economic growth should be incorporated in the calculus of policy maker.

This paper will not directly look at the effect on productivity and labor outcomes. We can argue conducting studies about the relationship between pollution reduction and the gain of working hour is ambiguous and complex. High level of pollution may indeed cause temporary illness which in turn may reduce employment and cause lost working hours (Hanna and Oliva, 2011). However, Hanna and Olivia rightly advocate individuals already practice mitigating behaviors on high pollution days to minimize illness. The effect of pollution may then not be large enough to interfere with attendance at work. The endogeneity may also be an important issue. Whereas pollution affects labor, a decline in business activity may affect pollution level and employment patterns (Chay and Greenstone, 2003). Strikes at oil refineries are a good example as it reduces both working hours and pollution emission.

In comparison, the effect of health on labor outcomes is much more obvious and can be extrapolated from an effect of air pollution on health. We may indeed more easily assume from the previous literature that health induces absenteeism (Currie et al., 2009). The Result section gives a monetary evaluation of the labor cost induced by pollution concentration. Besides, individuals may also gain other benefits from improved air quality. Expenditure on some good may go down when experiencing better health. We may observe a substitution effect from health related goods to consumption leisure. Welfare gains for cleaner air should not be ignored. This is in line with cost benefits analysis research.

3.2 Social distribution of pollution

To identify the social distribution of air pollution, the study compared the social characteristics (income, unemployment, population size) and the concentration of air pollution among town. Not surprisingly, locations that neighbored the areas where the refineries shutted down also experienced air quality improvements. On the other hand, census districts that did not have refineries and did not neighbor such census districts experienced minimal pollution changes [9]. In this context, we first may wonder whether area close to refineries are also the ones with low socioeconomic level. Poor people may be more likely to live where the pollution is, next to industrial area where are the refineries. It is cheaper to live for poor people. Due to budget constraint, the unemployed people are also less likely to move from one area to another to avoid pollution. Secondly, we also ask oneself if a change in pollution benefits, in term of health, even more to high socioeconomic than low levels areas. We look at the difference in exposure versus the difference in sensitivity. Our first stage estimation focuses on the difference in exposure to air pollution: reduction in air pollution following an exogenous shock is more important in richer area. Our second stage estimation looks at the difference of impact on health from a reduction in air pollution comparing unemployed area from the ones with an higher level of employment. The main purpose is to figure out if inequalities tend to mount up within french census districts. Assume refineries closure had an effect on the number of admissions that was independent of the health gains from reduced pollution levels, and that this effect is a function of the socioeconomic characteristic [10]. The health independent effect of the refinery closure on the number of admissions should have been nearly identical for all individual within the census tract where the refineries are. Now assume geographical area where refineries are, have low socioeconomic status whereas its counterpart have an high socioeconomic status. The health effect of a decrease in air pollution may be all the more significative because poor area is concerned. Poorer the area is, bigger the health effect of an increase in air pollution? Do we face a poverty trap?

[9] This change in pollution is represented in Figure 1

[10] We may think people have more time to dedicate to go to see the doctor as they are not working this day. They may decide to go to hospital for a regular check-up

4 Dataset presentation

4.1 Pollution data

Air quality is monitored throughout France (mainland and overseas departments) by 38 approved air quality monitoring associations (AASQA). The French monitoring station system counts approximately 700 measurement stations equipped with automatic instruments and nearly 400 experts implement this monitoring system. We focus on sulfur dioxide (SO_2). We obtain daily measure of ambient air pollution concentrations in microgram per cubic meter ($\mu g/m^3$) for all air quality monitors in France for 2007-2010 from the Ministry for Ecology, sustainable development and spatial planning (ADEME) database. Monthly pollution concentration data are presented in Panel A of the summary statistics where we also present our constructed measure of expected exposure to SO_2 . The first line of Panel A shows that we are well below this threshold in October 2010 as the maximum daily average is less than 100 $\mu g/m^3$ [11] . Over 35124 census tracks for patients, only 501 have at least one monitoring station. However, we will not consider all of them. Some monitoring stations do not measure SO_2. In addition, I remove monitoring stations that do not exist for the entire period: from 2007 to 2010. As we will also take into account the interaction between weather and pollution, we remove department with air pollution monitoring stations but without weather monitoring stations [12]. These 44 departments represent 156 census tracts and 187 air pollution monitoring stations. [13]

4.2 Morbidity data

Health data are drawn from the French National Hospital Discharge Database (PMSI) from 2007 to 2010. The key variables for our analysis are the month of admission , the length of stay and the place of residence of the patient. We dispose of an anonymous summary which gives information about the geographical code of residence of a patient, its age, its sex, its main and linked diagnosis. Pathologies are classified with respect to the international disease classification. We dispose of both outpatient discharge admission and emergency admission. People who did not stay overnight in the hospital have a length of stay of zero in the dataset. We do not dispose of the exact day of admission but we have the length of stay. We will use this information to construct our measure of expected exposure to air pollution. Panel C of the summary statistics sheds light on the number of admissions for respiratory

[11] The daily threshold fixed by european act is 125 $\mu g/m^3$ not to overcome more than 3 days a year.

[12] By doing so, the number of local authorities with monitoring stations is reduced from 95 to 44 "department". The department we are not going to consider are: 2, 3, 4, 5, 8, 9, 11, 12, 15, 20, 23,24, 28, 32, 36, 41, 43, 45, 46, 47, 48 53, 58, 61, 70, 72, 78, 82, 83, 84, 86, 90,91, 95.

[13] There is still a difference in observations because there is a difference in the number of measures taken every day or some days are missing. For instance, PM10 has more than one observation for one day for the same station.

disease by month, year and census track. We also consider the number of admissions with respect to age and sex. Note that most of our dataset consist of patients that have stayed less than 15 days (90 percent).

4.3 Weather data and socioeconomic data

We use temperature, precipitation, humidity and wind data in our analysis to both control for the direct effects of weather on health (Deschenes et al., 2009) and also to leverage the quasi-experimental features of wind direction and wind speed in distributing pollution from refineries (Hanna and Oliva, 2011) (Schlenker and Walker, 2011). Our weather data come from Meteo France, the French national meteorological service. We dispose of the average and maximum temperature in Celcius degree, the number of precipitation in millimeters, the maximum speed wind in meters per second, the prevailing wind direction in wind rose and the maximum and minimum relative humidity in percent [14]. We use data a daily frequency from the French weather monitoring system. We dispose nearby one station by census tract and we mainly use it as a control in the regression. Weather data are presented in Panel C of the summary statistics.

Temperature and the intensity of sunlight play an important influence in the chemical reactions that occur in the atmosphere to form photochemical smog from other pollutants. Besides, Wind speed and direction measurements are important for air quality monitoring. If high pollutant concentrations are measured at a monitoring station, the wind data recorded at the station can be used to determine the general direction and area of the emissions. Wind speed can greatly affect the pollutant concentration in a local area. The higher the wind speed, the lower the pollutant concentration. Wind dilutes pollutants and rapidly disperses them throughout the immediate area. Humidity and precipitation can also act on pollutants in the air to create more dangerous secondary pollutants, such as the substances responsible for acid rain. Precipitation can also have a beneficial effect by washing pollutant particles from the air and helping to minimize particulate matter formed by activities such as construction and some industrial processes.(Environmental Protection Agency (EPA), 2012a).

We also use the quarterly rate of unemployment from the National Institute of Statistics and Economic Studies (INSEE). Figure 2 shows that the Unemployment rate is smaller in census blocks where refineries are which contradicts the idea that refineries may be placed predominantly in poorer neighborhoods. The graph also indicates there is no trend difference between census blocks with refineries and their counterparts within the same department. Unemployment is decreasing over the period for all the territory. We also look

[14]The relative humidity of an air-water mixture is defined as the ratio of the partial pressure of water vapor in the mixture to the saturated vapor pressure of water at a prescribed temperature.

at a revenue variable for households. Controlling for income may be particularly important since, although small when compared to the pollution shocks, we can face differential income shocks across census districts (Chay and Greenstone, 2003). In addition, income is believed by many to have a direct effect on health (Ettner, 1996).

4.4 Matching health and pollution data

We merge the respiratory hospital admissions dataset with the ambient air pollution dataset by month from 2007 to 2010 at a census track level with respect to sex and age. We aggregate the daily measure of ambient air pollution monthly in order to merge the pollution database with the health database. The idea is to look at the link between pollution exposure and the number of hospital admissions with respect to age and sex. The next section details how exactly we derive a measure of exposure to Sulfur dioxide (SO_2).

We look at 4 stations which totally shutted down for nearby 15 days in October 2010. The monitoring stations next to the refinery are industrial ones. There is a tradeoff between including areas that are far from a monitor where pollution estimates are imprecise and including more observations in the analysis. Thus, we first estimate our model considering the entire dataset. Then, we reduce the dataset looking at census blocks within eight kilometers of a monitoring station. We compare the monitoring station next to refineries to their counterparts. [15] The census track corresponding to Gonfreville l'Orcher, one of the refinery which shutted down, does not exist in the health dataset, so that, we consider there is none admissions for this census tract. The closest census block measuring SO_2 is far away Gonfreville l'Orcher. Not to bias our estimate, we have to remove this station from our study. We also attribute a zero to all census tracks with pollution measure but without respiratory admissions. We also cannot consider the Grandpuits refinery because there is no air pollution monitoring station next to it. We first merge both dataset by census tracks. Besides, most of the census blocks do not have monitoring stations. Only 501 census blocks have at least one monitoring station. As we do not want to lose too much information, we do a second merge assigning pollution with respect to the department, for census tracks without monitors. We end up with 3 100 census tracks in our dataset.

5 Empirical Methodology

Our goal is to assess the impact of air pollution reduction on health outcomes for those census tracks that experienced a reduction in air pollution following strikes at oil refineries

[15] The 69, 79 and 44 departments have 23, 4 and 17 air pollution monitoring stations respectively similar from 2007 to 2010 and 2, 1 and 1 weather monitoring stations respectively. We end up looking at 11, 1 and 1 air pollution monitoring stations for those departments where the information at the insee code level is also available for weather.

in October 2010. Since we have a panel dataset, the best way to isolate causal effect of the reduction in SO_2 concentration from the strikes at oil refineries is to examine outcome differences between census tracks with refineries from their counterparts overtime. To begin, we calculate a measure of expected exposure to air pollution.

5.1 Expected exposure

We implement a two-step procedure to create a measure of expected exposure to air pollution that we describe in this section. First, we will derive a measure of exposure to ambient air pollution with respect to the length of stay (LOS). Second, we weight this measure of exposure by the distance existing between the monitor and the center of each census tract.

First, the health database does not give the exact day of admissions. We dispose of the month of admissions and the length of stay expressed in number of days for each patient. According to the length of stay, a patient can be admitted either the same month than the month of discharge or the previous one. Due to this uncertainty, we derive a measure of exposure using the month of discharge and the length of stay assuming that the month of admissions and the month of exposure are similar. The empirical literature provide evidence for potential impacts of short term exposure (5-10 minutes) of SO_2 on respiratory symptoms (World Health Organization (WHO), 2005). Peel et al. find a stronger risk ratios for asthma for a lag of 5 to 8 days studying pollution levels and emergency visits, (Peel et al., 2007). Thus, it seems reasonable to consider that we may go to the hospital few days after being exposed. We then define our measure of pollution exposure E_{cm} given the month of discharge m for individual i at census track c as a sum of probability of air pollution exposure as follows:

$$E_{cm} = P_{c,m}Pr(m|LOS) + P_{c,m-1}Pr(m-1|LOS)$$

$P_{c,m}$ represents the aggregated monthly measure of sulfur dioxide (SO_2) in micrograms $/m^3$. $Pr(m|LOS)$ represents the probability of being exposed to air pollution (or being admitted) in month m given the length of stay LOS. It is the probability a patient has been exposed in month m, given m the same month of discharge, if he has stayed up to 30 days. It is also the probability it has been exposed in month m-1, given m the month of discharge, if he stayed between 30 and 60 days and so on. On the other hand, $Pr(m-1|LOS)$ represents the probability a patient has been exposed in month m-1 given the length of stay. It can be the probability it has been exposed in month m-1 given m, or the probability it has been exposed in m-2 given m and so on. We repeat this process until reaching the maximum length of stay in our dataset which is 999 days. Thus, we have 33 intervals up to a length of stay of 1020. Longer a patient has stayed in the hospital, smaller is the probability it has been admitted the same month than the month of discharge. On the contrary, if a patient has stayed few days, we may imagine that the probability of being admitted the same month than the month of discharge is higher than the probability of being admitted the previous month than the month of discharge. For instance, a patient who did not stay overnight and only has come for an emergency have a probability of one of being admitted the same month than the month of discharge. Annex 1 details the construction of this measure of expected exposure.

The second step of our measure of exposure to ambient air pollution involves using the location (i.e., latitude and longitude) of each monitor, within each census tract. Following Currie and Neidell (Currie and Neidell, 2004), we created census block-specific measures of pollution using the inverse of the distance to the nearby stations as weights [16]. We then obtain a weighted average of the readings. The result of this second step is a census tract-level measure of air pollution.

5.2 Estimation

We are looking at the causal relationship between a slowdown in the refining activity, local pollution levels, and the number of contemporaneous respiratory hospitalizations in France. Our purpose is to estimate the number of hospital respiratory admissions Y_{cm} with respect to expected exposure E_{cm} or the parameter β_1 in the following linear probability model:

$$Y_{cm} = \beta_0 + \beta_1 E_{cm} + \underbrace{W_{cm} + \theta_m + \eta_y + \eta_c}_{X_{cm}} + \epsilon_{cm} \quad (1)$$

where the dependent variable Y_{cm} represents the number of respiratory admissions within each census tract c at month m . E_{cm} is the expected exposure to ambient air pollution described previously for census tract c and month m [17]. X_{cm} is a vector of census tract controls that include weather controls W_{cm}. We also control for temporal variation in pollution including month fixed effects θ_m, year fixed effects η_y to limit the influence of pollution outliers. We also include in all regression a census tract fixed effect η_c to control for time-unvariant unobserved covariates of the number of respiratory admissions. ϵ_{cm} represents the error term. This model requires:

$$\mathbb{E}[\epsilon_{cm}, E_{cm}] = 0 \quad (2)$$

However, we have many reasons to believe the assumption of no correlation between the errors and the measure of pollution exposure does not hold. This source of endogeneity increases the amount of measurement error. This could occur, for example, if weather adversely affected the number of hospital admissions activity while also affecting the level of sulfur dioxide (SO_2). To deal with the problem of omitted variables, we use the exogenous

[16] where the weights vary with the distance between the monitor and the center of the census tract.

[17] because we dispose of monthly hospital admissions , we aggregate our daily measure of pollution concentration at a monthly level

variation in pollution from the refinery closure. We estimate the following model using an instrumental variables approach instrumenting for pollution with $(oct2010 \times treatment)$:

$$E_{cm} = \alpha_0 + \alpha_1(oct2010 \times treatment) + \delta X_{cm} + \mu_{cm} \tag{3}$$

$$Y_{cm} = \beta_0 + \beta_1 \widehat{E_{cm}} + \delta X_{cm} + \upsilon_{cm} \tag{4}$$

where Oct2010 is an indicator for the month of the refinery closure and treatment is a dummy variable for whether the census tract of the air pollution monitoring station is located where the refineries are. The expected exposure E_{cm} is weighted by the distance between the monitoring station and the center of the census tract as we decribed in the previous section. We use the instrumented expected exposure $\widehat{E_{cm}}$ as predicted by the first stage (equation 3) to investigate the potential links between exposure to air pollution and short term health effects. We estimate a two-stage least-squares regression model. The panel structure of the data allows for additional controls X_{cm} that purge the effect of the refinery closure of any bias associated with differential census tract trends. In equation 4, υ_{cm} represents all unobserved determinants of the number of admissions. β_1 is unbiased if conditional on seasonal pattern, year, month and census block fixed effect, there are no unobserved covariates of health that change differentially during the closure:

$$\mathbb{E}[\upsilon_{cm}, (oct2010 \times treatment)|X_{cm}] = 0 \tag{5}$$

Finally, we exploit additional within neighborhood variation in pollution to isolate the health channel from other localized effect from the refinery closure. To do so, we estimate models similar to (3) and (4), where we interact the refinery closure with wind direction and wind speed. The idea is that wind direction and wind speed transport pollutants accross space. Assume the closure has an effect on the exposure to air pollution and that this exposure to air pollution faded away as a function of the distance to the monitoring station. the effect of exposure to air pollution on hospital admissions will also be a function of the distance to the monitoring station. The health effect must be nearly identical for all individual within the same distance. Assume now different wind pattern such that exposure to air pollution could be greater up north of the census tract than up south. Therefore, wind patterns interact with refineries closure and the timing (October 2010) in order to produce variation in pollution levels that is independent from any other localized direct effect of the refinery closure. We can write the model as follows:

$$E_{cm} = \alpha_0 + \alpha_1(oct2010 \times treatment \times W_{cm}) + \delta X_{cm} + \mu_{cm} \tag{6}$$

$$Y_{cm} = \beta_0 + \beta_1 \widehat{E_{cm}} + \delta X_{cm} + \upsilon_{cm} \tag{7}$$

We instrument for pollution with $(oct2010 \times treatment \times W_{cm})$. The sign of the coefficient are not so intuitive (Schlenker and Walker, 2011). Larger wind speed both clean the air and carry greater amount of pollutant further distance.

6 Empirical Results

6.1 First stage: Refinery closure and local pollution level

We start by examining the effect of strikes on air pollution. Figure 1 provides a daily graph of SO_2 residual estimation from september to december 2010 for census blocks within and beyond the census tracks where refineries are. We control for seasonal patterns adding year and month dummies to deal with the falling pollution trend and the high variation in air pollution we observe overtime. Influencing the general direction and dispersion of the pollutant, weather patterns have also great bearing on air pollution. Thus we also include a vector of weather variables. Air pollutants are influenced by the movements and characteristics of the air mass into which they are emitted. After the closure of the 4 refineries, pollution falls in census blocks where the refineries are relative to their counterparts where refineries are not. Table 2 details this effect. The result is interesting in itself to understand to what extend the refining activity influences the amount of pollution released in the air. We present the estimate of α_1 from Equation (3), where we replace the treatment variable by a dummy variable whether the census block is located where refineries which shutted down are. We consider first a simple measure of SO_2 in Micrograms per cubic meter in column 1. Then, in column 2 we consider our constructed measure of expected exposure to air pollution with respect to the length of stay but without taking distance into account. In the last three columns, we take full advantage of the variation in distance between the census block and the monitoring station using a measure of expected exposure taking both distance and length of stay into consideration [18]. Column 4 replicates the analysis in column 3 but we additionaly include demographic controls - an indicator variable for gender and age and a variable for the unemployment rate. The last column reduces the dataset to eight kilometers distance between the centroid of the census block and monitors. Note that all specifications include month, year and census block fixed effect and are clustered by census block and month.

Census blocks located where refineries are, show a reduction in SO_2 air pollution during the period of strikes. Refineries closure substantially reduces pollution and it is consistent with all measure of pollution. The estimate is not driven by standard demographic characteristics (column 4) nor by neighborhood specific trends (census block FE). Taking distance into account increases the magnitude of the effect and the estimate remains significant at the ten percent level. The effect rises too when patient are closer from the refineries. Note R-squared is also increasing by looking at our measure of expected exposure to air pollution giving more credibility to our index. We will focus on this measure for the next estimations.

[18]the construction of this measure of exposure is more precisely described in the previous subsection

6.2 Reduced form: Effect of refineries closure on local respiratory outcomes

We now focus on the health impact evaluation of a refinery closure. Results from the reduced form are important because refinery closure may involve benefits (Hanna and Oliva, 2011). The model below may help to establish the extent to which refineries closure reduces economic costs in the form of earning profits and wages. We estimate the direct effect of strikes on the number of hospital respiratory admissions as follows:

$$Y_{cm} = \beta_0 + \beta_2(oct2010 \times treatment) + \delta X_{cm} + \upsilon_{cm} \tag{8}$$

We present the estimate of β_2 from Equation (8) in Table 3. Column 2 adds controls for demographics while column 3 presents a reduced dataset and reports impacts at a distance of maximum 8 kilometers between the centroid of the census block and the monitors. We also divide our estimation with respect to age category in Table 4. All specifications include month, year and census block fixed effect, demographic controls and are clustered by census block and month.

Strikes reduce significantly the number of hospital admissions. This effect increases when taking distance into account. Results are particularly robust for at risk population: children below 5 years old and adults above 70 years old. The economics literature recognizes that poor health in childhood might depress children's human capital building (Grossman and Kaestner, 1997). Most of a person's human-capital and physiological development happens indeed early in life. Childhood is thus a key period for human-capital accumulation, and the burden of disease in childhood could have effects that persist throughout the lifetime. Strikes also reduce the number of hospital admissions for people between 40 and 60 years old. This last category is part of the working population [19]. We are in line with the literature saying that pollution significantly reduces worker productivity through health. Thus, cleaning up pollution from refining activity would benefit the economy in term of labor. This result suggests that workers with young children are even more likely to miss a day of work because pollution impacts their own health and their children's ones [20].

[19] Note that we find a significant result for three categories of age where the sample is bigger. The lack of significativity may come from a lack of observations for the other categories

[20] The extent to which workers miss work due to high pollution level may also vary by demographics and job types. If we think about children , the effect of pollution on absenteeism at work between men and women may differ. Women may indeed be more likely to stay at home if their children are sick. In this case, lower pollution level leads to an increase in the number of hours worked if children are in better health.

6.3 Hospital respiratory admissions and Instrumented pollution Exposure

We now relate hospital admittance, both emergency and overnight stays, for the overall population to instrumented pollution level at census blocks level. Table 5 presents the IV estimates of the number of respiratory hospital admissions with respect to expected exposure to air pollution. In every column, the number of respiratory hospital admissions is the outcome of interest. The first stage estimates for each of these columns corresponds to those presented in Table 2. Column 1 reports the impact of the expected exposure to air pollution with 2SLS estimation for the entire dataset controlling for seasonal patterns. Column 2 includes demographic controls and column 3 reports impacts at a distance of maximum 8 kilometers from the monitors. As outlined previously, all specifications include month, year and census block fixed effect and are clustered by census blocks and month.

Refineries closure provides a significant and relatively clean source of variation in local pollution impacting significantly the number of hospital admissions. It suggests Sulfur Dioxide, at levels below the standard at which public authority considers health can be harmed, has a delerious impact on respiratory outcomes. The coefficient estimates are similar in magnitude and significance when controlling for demographic characteristics (column 2). When we reduce the dataset to a distance between the patient and the monitors to maximum 8 kilometers, the effect size is the same. Last, Table 6 presents the interaction with wind patterns. Interacting refineries closure with wind speed reduces slightly the effect of strikes on the number of respiratory hospital admissions.

To sum up, these results are robust to a very strict test of endogeneity. This is all the more relevant giving the narrow time shock of 15 days. As such these findings indicate that estimated effects do not appear to be driven by any local shocks from the closure or differential migration into the area that saw the sharpest reduction in pollution.

6.4 Monetary evaluation

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We derive an approximation of the cost of pollution in term of labor by looking at the cost of hospital admission. The ExternE project gives a monetary evaluation that we take into account to derive an approximation of the cost of pollution [21]. The cost of one hospital admission and one emergency room visit for respiratory illness is evaluated at 2 000 Euros per admission and 670 Euros per visit respectively (price year 2000) (Bickel et al., 2005). The effect size that we find suggests that 1 $\mu g/m^3$ of sulfur dioxide pollution leads to an increase of 0.00469 respiratory admission for patient at a maximum distance of 8

[21] The ExternE project aims to measure the damages to society which are not paid for by its main actors and to translate these damages into a monetary value.

kilometers from the monitor (Table 5 - Column 3) [22]. If we increase pollution by a little bit more than 210 $\mu g/m^3$, there is one more hospital respiratory admission . The daily pollution concentration varies between 0 to 506 $\mu g/m^3$ from 2007 to 2010 for SO_2. Thus, there is a difference of almost 3 respiratory hospital admissions between minimum daily pollution concentration and maximum daily pollution concentration from 2007 to 2010. As one day of hospital respiratory admission costs 2 000 euros and the average length of stay for respiratory hospital admission in the dataset is 7 days, there is a cost difference of nearby 42 000 euros (2000*7*3) between days with pollution and days without pollution. The daily average maximum concentration of Sulfur dioxide varies between 92 to 218 $\mu g/m^3$ between the last 15 days of october before 2010 and in 2010. As a consequence, the maximum daily concentration during the period of strikes has been reduced by 126 $\mu g/m^3$. It induces, with our approximation, a hospital cost reduction of 8 400 euros between the maximum daily pollution concentration from october 2007 to 2009 and the maximum daily pollution concentration in october 2010 during strikes (2000*7/210*126). Table 1 indicates that there is a mean difference of nearby $1.8\mu g/m^3$ in the daily average concentration of SO_2 for the 15 days of strikes between 2007 to 2009 compared to 2010. Thus, it implies an increase of 3 hospital admissions over one year(0.00469*1.8*15*24) which is again a cost over 42 000 euros . Note that we underevaluate these costs due to the monthly average we used for our estimation [23].

7 Conclusion

This paper tests the short term effect of Sulfur Dioxide (SO_2) on respiratory outcomes. Our goal is to assess the impact of air pollution reduction on health outcomes for those census tract that experienced a reduction in air pollution following strikes at oil refineries in October 2010. Since we have a panel dataset, the best way to isolate causal effect of the reduction in SO_2 concentration from the strikes at oil refineries is to examine outcome differences between census tract with refineries from their counterparts overtime. We look at the effects of strikes on local measures of pollution. We adress several longstanding issues dealing with non-random selection and behavioral responses to air pollution that may bias previous studies. Our results indicate that SO_2, even at levels below current air quality standards in most of the world, has significant negative impacts on health disease, suggesting that the strengthening of regulations on SO_2 pollution would yield additional benefits. This result is particularly significative for at risks population such as children

[22] This result comes from the first stage and the reduced form which suggest strikes reduces both pollution by 17 $\mu g/m^3$ and the number of hospital respiratory admission by 0.08 (17/0.08=0.00469).

[23] The monthly average for the concentration of pollution tends to reduce the real impact of pollution in the estimation

below 5 years old and people over 70 years old. We also find a significative effect for adults between 40 and 60 years old suggesting air pollution concentration can have a delerious impact on labor outcomes. Future research should focus on longer term effect of SO_2 air pollution concentration on health outcomes.

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Appendix 1

We derive a a measure of Expected exposure in section 5 as a sum of probability of air pollution exposure.

$$E_{cm} = P_{c,m} Pr(m|LOS) + P_{c,m-1} Pr(m-1|LOS)$$

And we describe our probability of air pollution exposure as follows:

$$Pr(m|LOS) = \begin{cases} Pr(m|LOS = LOS_0) = P(m|m) \text{ if LOS } \leq 30 \\ Pr(m|LOS = LOS_1) = Pr(m-1|m) \text{ if LOS } \in [30;60] \\ Pr(m|LOS = LOS_2) = Pr(m-2|m) \text{ if LOS } \in [60;90] \\ Pr(m|LOS = LOS_3) = Pr(m-3|m) \text{ if LOS } \in [90;120] \\ ... \\ Pr(m|LOS = LOS_n) = Pr(m-(n)|m) \text{ if LOS } \in [990;1020] \end{cases}$$

$Pr(m|LOS)$ represents the probability of being exposed to air pollution (or being admitted) in month m given the length of stay. It is the probability a patient has been exposed in month m, given m the same month of discharge, if he has stayed up to 30 days.

$$Pr(m-1|LOS) = \begin{cases} Pr(m-1|LOS = LOS_0) = Pr(m-1|m) \text{ if LOS } \leq 30 \\ Pr(m-1|LOS = LOS_1) = Pr(m-2|m) \text{ if LOS } \in [30;60] \\ Pr(m-1|LOS = LOS_2) = Pr(m-3|m) \text{ if LOS } \in [60;90] \\ Pr(m-1|LOS = LOS_3) = Pr(m-4|m) \text{ if LOS } \in [90;120] \\ ... \\ Pr(m-1|LOS = LOS_n) = Pr(m-(n+1)|m) \text{ if LOS } \in [xmin;1020] \end{cases}$$

$Pr(m-1|LOS)$ represents the probability a patient has been exposed in month m-1 given the length of stay. It can be the probability it has been exposed in month m-1 given m, or the probability it has been exposed in m-2 given m and so on.

The sum of expected exposure to air pollution with respect to LOS corresponds to:

$$\sum_{n=0}^{33} E_{cm} = \sum_{n=0}^{33} [P_{cm} * Pr(m|LOS = LOS_n) + P_{c,m-1} * Pr(m-1|LOS = LOS_n)]$$

$$= \sum_{n=0}^{33} [P_{cm} * Pr(m-(n)|m) + P_{ic,m-1} * Pr(m-(n+1)|m)]$$

$$= \sum_{x=0}^{1020} [P_{cm} \frac{1-(LOS - xmin)}{30} + P_{ic,m-1} * \frac{LOS - xmin}{30}]$$

Table 1: Summary statistics (N= 813 466)

Variables	**Mean**	**Std. Dev.**	**Min.**	**Max.**
	Panel A : Pollution concentration			
Sulfur dioxide (SO_2) ($\mu g/m^3$)				
Daily average 12th to 30th of Oct 2010	2.803911	5.355692	0	92.21739
Daily average 12th to 30th of Oct from 2007 to 2009	4.577996	9.491864	0	218.2083
Monthly average from 2007 to 2010	2.439	2.605	0.042	53.337
Expected_Exposure	2.434	2.604	0	53.337
Expected_Expo_Distance	3.769	87.326	0	5333.044
	Panel B : Health outcomes			
Nb_Resp_Ad _Age_Sex	1.147	0.481	1	16
Nb_Resp_Ad	25.192	37.391	1	325
	Panel C : Weather patterns			
Precipitations (mm)	2.245	1.403	0	10.309
Av_Temp (^0C)	10.982	5.944	-4.117	26.173
Max_Temp (^0C)	15.515	6.756	-1.9	32.356
Speed_Wind (m/sec)	7.132	1.42	3.1	16
Direct_Wind (wind rose)	207.28	38.918	65.599	312.414
Min_Humidity (%)	56.393	11.824	27.194	87.871
Max_Humidity (%)	92.652	4.184	70.412	100
	Panel D : Geographics and Demographics			
Age	54.355	30.615	1	109
Sex	1.445	0.497	1	2
Pop	35880.031	63180.355	179	439453
Unemployment rate (%)	9.246	2.23	3.8	17.1
Tax Revenue (Euros)	25958.072	5363.226	0	59765
Distance (km)	32.223	26.505	0.001	393.76 [a]

[a]Notes: This table provides monthly means for the key variables in the regression analysis as well as standard deviations and minimum and maximum except for the first line which provides daily mean. Weather data comes from Meteo France. Pollution data comes from the French Ministry for Ecology, sustainable development and spatial planning (ADEME). Socioeconomic data were obtain from the National Institute of Statistics and Economic Studies (INSEE). Unemployment is defined as the quarterly unemployment rate

Table 2: First stage regressions

	(1)	(2)	(3)	(4)	(5)
Variables	SO2	Exp_expo	Expected_exposure_distance		
OCT2010_TREATMENT	-5.475*	-5.451*	-16.18*	-16.09*	-17.96*
	(3.200)	(3.196)	(8.406)	(8.412)	(9.379)
Precipitations	-0.0415	-0.0416	-0.0569	-0.0661	-0.208
	(0.0342)	(0.0342)	(0.0689)	(0.0770)	(0.298)
av_temp	-0.362***	-0.361***	0.258	0.204	0.998
	(0.134)	(0.134)	(0.553)	(0.599)	(2.617)
max_temp	0.325**	0.323**	-0.252	-0.228	-1.043
	(0.141)	(0.140)	(0.482)	(0.530)	(2.301)
speed_wind	-0.153**	-0.152**	0.221	0.267	0.988
	(0.0690)	(0.0689)	(0.151)	(0.173)	(0.651)
direct_wind	-0.00221*	-0.00220*	-0.00429	-0.00523	-0.0195
	(0.00128)	(0.00128)	(0.00372)	(0.00418)	(0.0171)
min_humidity	0.0452**	0.0450**	0.000841	0.00499	-0.00339
	(0.0221)	(0.0220)	(0.0387)	(0.0433)	(0.186)
max_humidity	-0.121***	-0.121***	0.0299	0.0224	0.0890
	(0.0288)	(0.0287)	(0.0368)	(0.0363)	(0.135)
Year FE	x	x	x	x	x
Month FE	x	x	x	x	x
Census block FE	x	x	x	x	x
Demographic controls				x	x
Distance<8km					x
Observations	813,466	813,466	812,537	723,424	184,064
R-squared	0.610	0.608	0.887	0.887	0.886 [a]

[a]Notes: This table provides the coefficient estimates of the effect of refineries closure on Sulfur Dioxide (SO_2). All regressions are estimated using OLS, with standard errors clustered at the month and department level. Demographic controls include an indicator for gender, age and the unemployment rate. Robust standard errors in parentheses. Statistical significance is denoted by: *** p<0.01, * p<0.05, * p<0.1

Table 3: Reduced form regressions

	(1)	(2)	(3)
Variables	Number_respiratory_admissions		
OCT2010_TREATMENT	-0.0771***	-0.0784***	-0.0844***
	(0.0152)	(0.0137)	(0.0156)
Precipitations	0.000190	0.000208	0.00135
	(0.000525)	(0.000547)	(0.00158)
av_temp	-0.00649*	-0.00811*	-0.0129
	(0.00301)	(0.00318)	(0.00933)
max_temp	0.00632*	0.00750*	0.0116
	(0.00281)	(0.00295)	(0.00881)
speed_wind	0.00191*	0.00252*	0.00257
	(0.000927)	(0.000977)	(0.00248)
direct_wind	4.35e-05*	4.30e-05	0.000162*
	(2.54e-05)	(2.68e-05)	(8.34e-05)
min_humidity	0.000455*	0.000560*	0.000208
	(0.000237)	(0.000250)	(0.000729)
max_humidity	0.000145	2.86e-05	-0.000114
	(0.000328)	(0.000343)	(0.000954)
Year FE	x	x	x
Month FE	x	x	x
Census block FE	x	x	x
Demographic controls		x	x
Distance < 8km			x
Observations	813,466	724,353	184,065
R-squared	0.099	0.100	0.111 [a]

[a]Notes: This table presents the coefficient estimates of the reduced form estimate of the effect of refineries closure on the number of respiratory admissions. All regressions are estimated using OLS, with standard errors clustered at the month and department level. Demographic controls include an indicator for gender, age and unemployment. Robust standard errors in parentheses. Statistical significance is denoted by: *** p<0.01, * p<0.05, * p<0.1

Table 4: Reduced form regressions by age category

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	0-5	5-15	15-25	25-40	40-60	60-70	>70
OCT2010_TREATMENT	-0.0789*	-0.0286	-0.0481	0.00530	-0.129*	0.00105	-0.0890*
	(0.0361)	(0.0421)	(0.0587)	(0.00746)	(0.0613)	(0.0454)	(0.0444)
Precipitations	0.00245	0.00295*	-0.000843	0.00118	-0.00110	-0.00213*	0.000710
	(0.00282)	(0.00170)	(0.00172)	(0.00138)	(0.000977)	(0.00129)	(0.000776)
av_temp	-0.0215*	-0.00486	0.00312	-0.000806	-0.000320	-0.0135***	-0.00896*
	(0.0115)	(0.00557)	(0.00802)	(0.00479)	(0.00348)	(0.00495)	(0.00436)
max_temp	0.0196*	0.00677	-0.00224	0.00161	0.000306	0.0133***	0.00829*
	(0.0105)	(0.00530)	(0.00752)	(0.00452)	(0.00336)	(0.00481)	(0.00410)
speed_wind	0.0107*	0.00420	0.00151	-0.00131	0.00209	0.00374	0.00120
	(0.00474)	(0.00286)	(0.00311)	(0.00224)	(0.00190)	(0.00229)	(0.00143)
direct_wind	9.72e-05	-9.59e-05	3.13e-06	7.05e-05	6.09e-05	-3.34e-06	5.33e-05
	(9.85e-05)	(6.28e-05)	(7.89e-05)	(5.63e-05)	(4.18e-05)	(5.68e-05)	(4.05e-05)
min_humidity	0.000153	0.000683	-0.000488	0.000256	-0.000130	0.00210***	0.000752*
	(0.00108)	(0.000774)	(0.000895)	(0.000643)	(0.000469)	(0.000680)	(0.000366)
max_humidity	0.000658	-0.000400	0.00143	-7.61e-05	0.00114*	-0.000722	-0.000239
	(0.00148)	(0.00110)	(0.00123)	(0.000840)	(0.000646)	(0.000834)	(0.000517)
Year FE	x	x	x	x	x	x	x
Month FE	x	x	x	x	x	x	x
Census block FE	x	x	x	x	x	x	x
Demographic controls	x	x	x	x	x	x	x
Observations	95,902	43,544	32,814	49,703	112,690	80,128	309,572
R-squared	0.340	0.133	0.111	0.092	0.089	0.104	0.122 [a]

[a]Notes: This table presents the coefficient estimates of the reduced form estimate of the effect of refineries closure on the number of respiratory admissions by age category. All regressions are estimated using OLS, with standard errors clustered at the month and department level. Demographic controls include an indicator for gender, age and unemployment. Robust standard errors in parentheses. Statistical significance is denoted by: *** p<0.01, * p<0.05, * p<0.1

Table 5: IV estimation

	(1)	(2)	(3)
Variables	Number_respiratory_admissions		
Expected_Exposure_Distance	0.00476**	0.00487**	0.00469*
	(0.00229)	(0.00245)	(0.00262)
Precipitations	0.000462	0.000531	0.00234
	(0.000627)	(0.000686)	(0.00220)
av_temp	-0.00778*	-0.00917**	-0.0176
	(0.00397)	(0.00430)	(0.0155)
max_temp	0.00758**	0.00868**	0.0165
	(0.00361)	(0.00391)	(0.0140)
speed_wind	0.000859	0.00123	-0.00206
	(0.00126)	(0.00144)	(0.00453)
direct_wind	6.40e-05*	6.86e-05*	0.000254**
	(3.27e-05)	(3.63e-05)	(0.000125)
min_humidity	0.000453	0.000538	0.000216
	(0.000303)	(0.000333)	(0.00113)
max_humidity	6.83e-06	-7.61e-05	-0.000521
	(0.000373)	(0.000386)	(0.00114)
Year FE	x	x	x
Month FE	x	x	x
Census block FE	x	x	x
Demographic controls		x	x
Distance < 8km			x
Observations	812,537	723,424	184,064
R-squared	-0.091	-0.104	-0.177 [a]

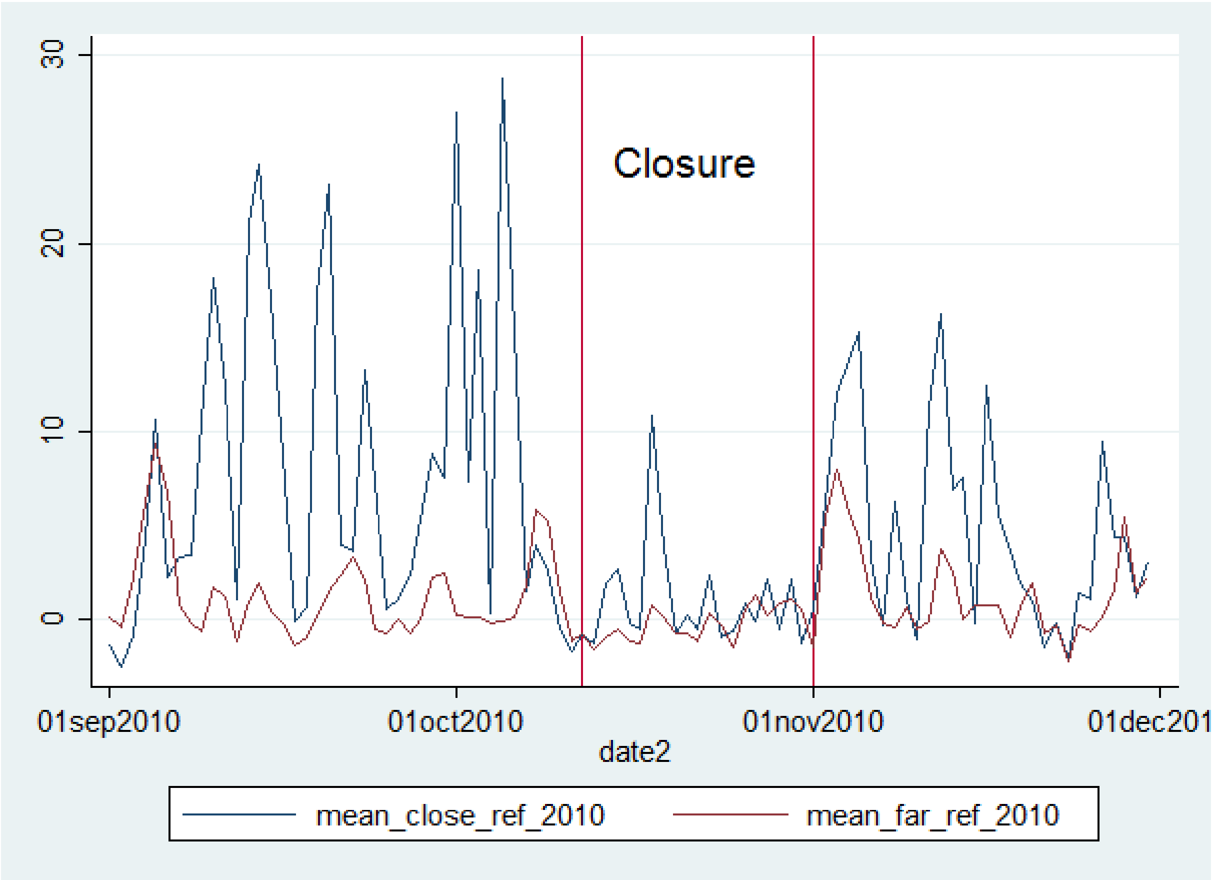
[a]Notes: This table presents the coefficient estimates of the IV estimate of the effect of Sulfur Dioxide on the number of respiratory admissions. All regressions are estimated using 2SLS, with standard errors clustered at the month and department level. Demographic controls include an indicator for gender, age and unemployment. Robust standard errors in parentheses. Statistical significance is denoted by: *** p<0.01, * p<0.05, * p<0.1

Table 6: IV Estimation with wind speed interaction

Variables	(1) Expected_expo_dist First stage	(2) Number_respiratory_admissions Reduced form	(3) IV
OCT2010_TREATMENT_Windspeed (as an intrument for Expected_Expo in (3))	-2.673**	-0.0109***	0.00406**
	(1.260)	(0.00217)	(0.00201)
Precipitations	-0.207	0.00132	0.00217
	(0.274)	(0.00150)	(0.00191)
av_temp	1.188	-0.00736	-0.0122
	(2.395)	(0.00873)	(0.0131)
max_temp	-1.125	0.00777	0.0124
	(2.078)	(0.00830)	(0.0119)
speed_wind	0.898	0.00146	-0.00216
	(0.584)	(0.00244)	(0.00367)
direct_wind	-0.0166	0.000157*	0.000225**
	(0.0158)	(8.05e-05)	(0.000106)
min_humidity	-0.0147	-0.000234	-0.000176
	(0.167)	(0.000695)	(0.000963)
max_humidity	0.134	0.000809	0.000276
	(0.141)	(0.000921)	(0.00109)
Year FE	x	x	x
Month FE	x	x	x
Census block FE	x	x	x
Demographic controls	x	x	x
Distance < 8km	x	x	x
Observations	202,260	202,261	202,260
R-squared	0.886	0.106	-0.123 [a]

[a]Notes: This table presents the coefficient estimates of the IV estimate of the effect of Sulfur dioxide on the number of respiratory admissions with respect to wind speed interaction. All regressions are estimated using 2SLS, with standard errors clustered at the month and department level. Demographic controls include an indicator for gender, age and the unemployment rate. Robust standard errors in parentheses. Statistical significance is denoted by: *** p<0.01, * p<0.05, * p<0.1

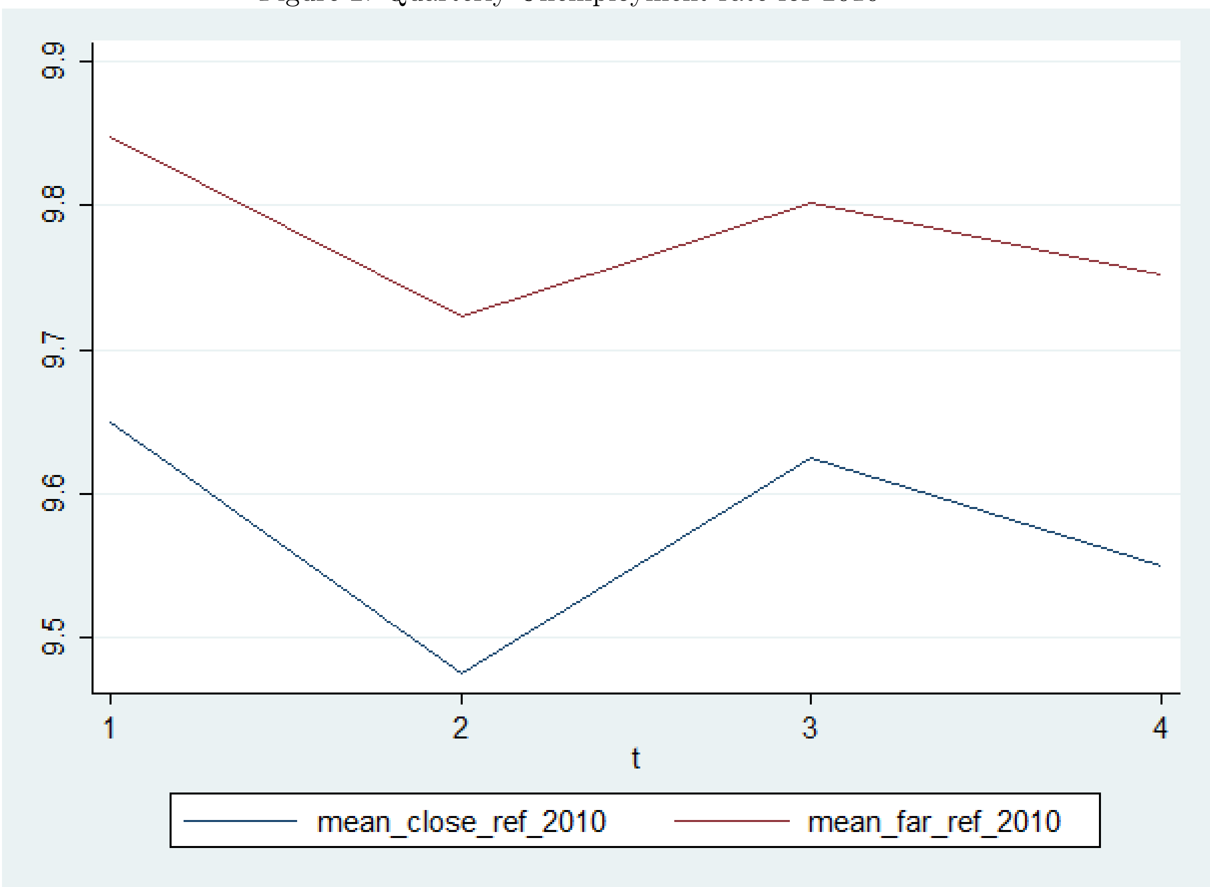
Figure 1: SO_2 residual regression for 2010



[a]

[a]Notes: This graph represents the SO_2 residual concentration for census blocks with a refinery versus census blocks without a refinery within the same department. The closure corresponds to the strikes at oil refineries in October 2010 from the 12th to the 30th of October.

Figure 2: Quarterly Unemployment rate for 2010



[a]

[a]Notes: This graph represents the quarterly average unemployment rate in 2010 for census blocks with a refinery versus census blocks without a refinery within the same department.