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Energy Production and Health Externalities: Evidence from Oil Strike Refineries in France

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Abstract: This paper examines the external effect of energy production on newborn health using a recent strike affecting oil refineries in France, in October 2010, as a natural experiment. First, we show that the temporary reduction in refining lead to a significant reduction in sulfur dioxide (SO2) concentrations. Second, this shock also significantly increased birth weight and gestational age of newborns, particularly for those exposed to the strike during the third trimester of pregnancy. Back-of-the-envelope calculations suggest that a 1 unit decline in SO2 leads to a 195 million euro increase in lifetime earnings per birth cohort. This externality from oil production should be an important part of policy discussions surrounding the production of energy.

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1. Introduction

Meeting the continued increased demand for energy is a major issue faced by nearly all countries. While there is much interest in developing renewable sources of energy, oil remains the predominant source given its relative price. Its portability also makes it particularly attractive for mobile sources, suggesting a reprieve in energy demand is unlikely in light of the tremendous growth in automobile ownership and travel throughout the world.

The production of energy from oil refineries, however, poses a health risk. The point source emissions include several pollutants linked with numerous health impacts, most notably sulfur dioxide (SO2). In some countries, such as France, nearly 20 percent of ambient SO2 emissions come from oil production (Soleille, 2004). Evidence links SO2 with a wide range of respiratory effects, and as such is regulated under the Clean Air Act. The optimal design of energy policy must consider this production externality when comparing its full costs to those from renewable energy production.

In this paper, we estimate the health externalities from oil production by exploiting the oil refinery strikes in France in October 2010. The strikes provide a natural experiment that enables us to overcome the typical biases that arise from residential sorting. Amid nationwide protests over pension reform and broader concerns about oil industry practices in France, striking workers blocked fuel supplies, which resulted in a complete cessation of operations at several major refineries for nearly a month. As we demonstrate below, this lead to a sharp reduction in SO2 that quickly dissipated once the strike was resolved and production resumed. We exploit this temporal event to identify the health externalities from oil production, comparing outcomes in areas close to the refineries before and after the strike vs. during the strike, using areas far from the refineries as a control group.

While this is not the first study to use the closing of an industrial process as a natural experiment (Pope and Ransom, 1995; Hanna and Oliva, 2011), there are several important features in our design that limit threats to identification. Since France has universal health coverage (independent of employment status), the strike did not result in a change in health insurance status that might have affected the utilization of health care. Moreoever, the stoppage at the oil refinery was due to a strike and therefore only temporary, making it unlikely that workers relocated in search of new employment opportunities. More generally, since the strike was a nationwide one, any common behavioral responses in response to the strike, such as changes in leisure time, are accounted for by including a control group.

This paper adds to a growing body of economic evidence linking air pollution with health (Chay and Greenstone, 2003; Currie et al., 2009; Currie et al., 2011), with three distinct contributions. One, most studies focus directly on the impact of pollution per se, with relatively few focusing on the specific externality from emissions. Because emissions interact with ambient conditions to form pollution, focusing on emissions is particularly relevant policy wise because this is what technology permits to be regulated. Two, the handful of studies that focus on emissions typically focus on the consumption of energy, primarily from mobile sources or smaller scale fixed sources, rather than production of energy (Currie and Walker, 2011; Beatty and Shimshack, 2011; Moretti and Neidell, 2011; Schlenker and Walker, 2011). The production externality is empirically distinct from the consumption one, and hence represents a generally overlooked social cost from energy production. Three, pollution levels are often highly correlated across the three trimesters of pregnancy, making it difficult to reliably estimate the effect from exposure in each trimester. Because the strike led to a temporary decrease in pollution for less than a month, our research design allows us to more credibly explore the effects by trimester.

Using this natural experiment, we first demonstrate that although SO2 is considerably higher in areas close to the refineries, it falls significantly during the strike to levels comparable to areas far from the refineries. We do not find changes in pollution of other measured pollutants, a finding consistent with the change coming from the oil refineries. Turning to health outcomes, we focus on birth outcomes, which are strong predictors of future outcomes (Black et al., 2007; Currie, 2009).[3] We find that in areas affected by the strike, birth weight and gestational age increased by over a 3 and 1.5 percent, respectively. Our results suggest these effects are almost primarily driven by exposure during the third trimester of pregnancy, which is consistent with biological theories of fetal development

2. Background: Refineries, Air pollution and Health

2.1. Pollution and the refinery closure

Refineries are responsible for 20 percent of SO2 release in France (Soleille, 2004). Oil refineries convert crude oil to everyday product like gasoline, kerosene, liquefied petroleum. Crude oil contains relatively high quantity of sulfur, which leads to

[3] Focusing on infants also offers a methodological benefit because cumulative exposure can be more readily assigned.

the creation of sulfur dioxide when crude oil is heated at the refinery to produce fuel. The refining process also releases a large number of chemicals such as benzene, chromium and sulfur acid into the atmosphere.

France has 11 refineries that produce 89 million tons of petrol every year. The main 4 refining companies operating in France are Total, Shell, Esso and Ineos, located in the regions of Haute Normandie, Provence Alpes Côtes dAzur, 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 about the industry in France. As a result, production was reduced to a minimum or completely shut for nearly 18 days until the strike was resolved. Closing a refinery is a complex process that requires anywhere from 2 days to one week according to the size of the refinery, and a comparable time period to re-open. Thus, the reduction in SO2 is likely strongest between mid October and the beginning of November. We focus on the 4 refineries that completely shut down as a result of the strike.

2.2. Pollution and health

Sulfur dioxide (SO2) is one of a group of highly reactive gasses known as oxides of sulfur (SOx). The largest sources of SO2 emissions are from fossil fuel combustion at power plants and other industrial facilities (EPA 2011). SO2 is a colorless gas with a very strong smell. In France, the threshold for SO2, fixed by the European Act of 2002-13 related to air quality is 132 parts per billion (ppb) per hour; violations occur when this standard is exceed more than 24 times a year. In comparison, the Clean Air Act set the one-hour SO2 standard at 75 ppb, where a violation occurs if the 99th percentile of 1-hour daily maximum concentrations, averaged over 3 years, exceeds this value. This standard was recently strengthened in June 2010, suggesting the need for reliable estimates of the relationship between SO2 and health.

Given the rapid stages of development that a fetus goes through in a short period of time, negative shocks can results in both immediate and latent effects. Pollution is one potential shock because it can impair the health of the mother, indirectly compromising fetus health, or cross the placenta, directly affecting the health of the fetus. Slama et al. (2008) describe more extensively possible biological mechanisms by which air pollutants may affect birth outcomes. SO2 may be particularly harmful to the fetus because it can impact the blood viscosity, endothelial function, it creates hypertension and therefore has an effect on the placental blood flow, transplacental oxygen and nutrient transport. Furthermore, while there is a growing consensus that prenatal exposure affects birth outcomes, there is little understanding about the most susceptible periods of prenatal exposure. While the fetus experiences important organ developments in the first trimester, suggesting a particularly vulnerable stage, the fetus also grows the most during the third trimester, suggesting another crucial stage.

While not focused on SO2 per se, several economic studies have found robust evidence that prenatal exposure to pollution affects infant health (Currie et al., 2009; Sanders and Stoecker, 2011; Currie and Walker, 2011). While most of these studies focus on the effect from exposure during the entire pregnancy, an important contribution of our study is the ability to precisely estimate the effects from exposure during each trimester.

Furthermore, previous studies typically focus on pollution stemming from vehicular or industrial emissions, such as particulate matter and carbon monoxide, and our focus on oil refining is more relevant for SO2.

3. Data and empirical strategy

3.1. Data sources

Health data are drawn from the French National Hospital Discharge Database (PMSI) from 2007 to 2011. The key variables for our analysis are the year and month of birth, the place of residence of the patient, and the birth weight and gestational age at birth. Panel A of table 1 shows the birth weight and the gestational age by month, year and census track. We also consider low birth weight (<2500 grams) and short gestational age (<37 weeks) as two clinically relevant outcomes. We observe from table 1, panel A that the birth weight and gestational age are lower in the treatment group than in the group control for all periods of the study, hinting at potential effects from living near a refinery. Figure 2 shows the distribution of birth weight. Unlike the US, there is much less variation in birth weight in France.

Air quality is monitored throughout France by 38 approved air quality monitoring associations (AASQA). The French monitoring station system has approximately 700 measurement monitors equipped with automatic instruments. Figure 5 shows the location of monitoring stations as well as census tracts throughout France.

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. We also know the exact geographic location of each monitor. Since our main focus is on

SO2, we only include monitors that continuously measured SO2 during this time period. This leaves us with 187 monitors that span 44 departments (one of the three levels of government below the national level, between the region and the commune) and 156 census tracts. Monthly pollution concentration data are presented in Panel B of Table 1. We also present the mean of SO2 and PM10 pollutants when it exceeds the limit value for health.

Since weather has direct effects on health and also affects pollution formation, we also include meteorological data in our analysis. Our weather data come from Meteo France, the French national meteorological service. There are 100 monitors, one in each department. We also have daily measures at each monitor, along with data on the geographic location. We use average and maximum temperature, precipitation, maximum speed wind, prevailing wind direction, and maximum and minimum relative humidity. Summary statistics for daily and monthly measures of weather are presented in Panel C of Table 1.

Although we include census tract fixed effects in our regression, which controls for all time invariant characteristics, we also include one measure of economic well-being to capture time varying factors: the unemployment rate. We use the quarterly rate of unemployment from the National Institute of Statistics and Economic Studies (INSEE), which is available at the census tract level. Panel D of Table 1 also presents summary statistics for this variable.

3.2 Merging data

As with nearly all pollution-health analyses, there is important spatial dimension to consider when merging these data. We know the exact location of pollution and meteorology monitors, but only know the census tract of residence for the birth outcomes.

For the spatial merge, we assign pollution to census tracts in a two-step procedure. When a census tract has a pollution monitor in it, we assign that pollution concentration to the census tract. When it does not, we assign the average pollution concentration of all monitors within the department. We repeat this procedure for the weather data as well. Two, we assign pollution using an inverse distance weighted average (IDWA) of pollution, similar to Currie and Neidell (2005). To do this, we compute the centroid of each census tract, and then compute the distance from the centroid to each monitor within the department. We then take the weighted average of pollution measurements from all monitors within a certain distance from the census tract centroid, using the inverse of the distance as weights.

3.3 Empirical Methodology

Our goal is to assess the impact of oil production on both pollution levels and health outcomes at birth. We estimate difference in difference models to exploit the unexpected shutdown in production as a result of the strike in October 2010, using areas close to the refineries as the treatment group and areas far from the refineries as the control group. We implement this by estimating the following equation:

(1) $$Y_{cm} = \beta * strike_m * close_c + \delta * X_{cm} + \sigma_m + \alpha_c + \varepsilon_{cm}$$

where Y is either ambient pollution concentrations or health outcomes at birth in census tract c at month m. '*strike*' is an indicator variable for the October 2010 period when the strike occurred, and '*close*' is an indicator variable for whether the refinery is in the same census tract as the air pollution monitor or patient's residence. β is the difference-in-difference parameter. X_{cm} is a vector of census tract controls that include weather controls and, when focusing on respiratory admissions, the gender, age, and the quarterly unemployment rate. We control for seasonal and temporal patterns by including month dummies and year dummies in σ_m. We include census tract fixed effects (α_c) to control for time-invariant characteristics of the census tract. ε_{cm} represents the error term, which consists of an idiosyncratic component and a term clustered on the department and month.

As with any difference in difference design, the key underlying assumption for identification is that the control group serves as a valid counterfactual for the treatment group with parallel trends. Although we can not explicitly verify this assumption, we feel this threat is limited in this setting for several reasons. Because the strike was nationwide, and not just for the workers at oil refineries, any changes in response to the strike likely happened on a global scale that would have affected both the treatment and control groups. Moreover, the strike was a temporary condition, making it unlikely that workers would relocate in search of new employment opportunities. Furthermore, because workers in France have health insurance regardless of employment status, there was unlikely to be a change in health care consumption during the time of the strike.

Figure 3 provides evidence to support the parallel trends assumption. It plots unemployment rates over time for the treatment and control groups. Although the unemployment rate is smaller in census blocks with refineries, there is no trend difference between census blocks with refineries and their counterparts.

4. Results

4.1 Refinery closures and pollution levels

We start by examining the effect of strikes on air pollution. Figure 1 provides a daily graph of adjusted SO2 pollution from September to December 2010 for the treatment and control groups, with SO2 adjusted by X_{cm} and in σ_m. Prior to the strike, SO2 levels are considerably higher in census tracts with refineries. However, during the strike, SO2 dramatically falls in refinery areas to levels comparable to non-refinery areas. Immediately after the strike, SO2 levels in refinery areas again exceed those of non-refinery areas. This visual display clearly demonstrates a strong, temporal effect of the strike on SO2 levels.

Table 2 provides regression estimates of (1), which are largely analogous to this Figure. In order to gauge the extent of confounding, we successively add more time-varying controls, namely the weather variables and the unemployment rate. Consistent with Figure 2, the strike causes a statistically significant drop in SO2 levels for areas close to refineries. SO2 levels drop, during the last 15 days of October 2010, by roughly 15 μg/m^3. Adding controls for weather (column 2) and unemployment (column 3) has no noticeable effect on our estimates.

The second and third panels explore the effect from different approaches for assigning pollution from monitors to INSEE codes. Limiting the sample to INSEE codes within 8 km of a monitor, shown in panel 2, leads to a slight increase in the effect of the strike on SO2 levels. We see a much bigger increase, though still not a statistically significant difference, when we limit to INSEE codes with 2 km of a monitor. This increase is consistent a more precise measure of pollution from using a closer monitor. Overall, the results from Table 2 are largely consistent with those from Figure 1.

Figure 4 presents the same plot as Figure 1 for three additional pollutants: benzene, NO2, and PM10. While NO2 and PM10 do not appear to change in response to the strike, Benzene shows a pattern consistent with being affected by the strike, though less stark than that for SO2. While these patterns suggest SO2 is the pollutant most affected by the strike, the possible relationship for other pollutants precludes us from conducting an instrumental variable analysis where we instrument SO2 levels using the strike.

4.2. Refinery closures and respiratory outcomes

Given that we have found a relationship between the oil refinery strikes and pollution levels, we now turn our attention to the impacts of the strikes on health at birth. Table 3 presents results of the impact of strikes on birth weight and gestational age over the entire pregnancy. The top panel explores the effect on birth weight using the continuous measure and the low birth weight indicator, whereas the bottom focuses on gestational age and short gestation. Within each of the 4 dependent variables, we also explore sensitivity to controls as with the SO2 results, as well as sensitivity to monitor-INSEE code distance assumptions.

For birth weight, we find that birth weight increases by roughly 75 grams during the strike. This result is also insensitive to the addition of weather variables and unemployment. Compared to the mean birth weight of 3228 grams, this represents a 2.3 percent increase in birth weight. Using an indicator for low birth weight, we find that the strike lowered this rate by roughly 2 percentage points, which is also statistically significant and robust to additional controls. When we limit the distance from pollution monitor to the INSEE code to 8 km, our estimates change minimally, as with the SO2 results. Limiting to 2 km leads to a larger improvement in birth weight, though the difference is again not statistically significant.

For gestational age, we find similar qualitative results. Using all INSEE codes, regardless of distance to a pollution monitor, we find the strike increased gestational age by roughly 0.37 weeks, or 2.5 days, which is a 1% change from the baseline mean. The strike reduces the probability of short gestation by .08. These results are again insensitive to additional controls. While the results do not become larger when limiting to a shorter distance from the INSEE code to the pollution monitor, the differences are again not statistically significant.

Since the strike only lasted for less than one month, one of the advantages of our study is the ability to more precisely isolate the effects by trimester. Table 4 presents results by including exposure to the strike by trimester. We focus on just INSEE codes less than 8 km from a monitor, though results are quite comparable using other distances.

We continue to show the sensitivity of results to the meteorological and economic covariates, and again find these make little difference.

We find that almost all of the effects from pollution are due to exposure during the third trimester. Birth weight increases by roughly 150 grams when the strike occurred during the third trimester, which represents a 4.6 percent increase. The effects from the first and, in particular, second trimesters are much smaller and not statistically significant. Turning to the incidence of low birth weight, we find much similar effects across the trimesters, but only the third is statistically significant.

For gestational age, we also find that exposure to the strike in the third trimester has the biggest effect: it increases gestational age by roughly 0.85 weeks, a roughly 2.2 percent increase. The effects in the first and second trimester are again much smaller and not statistically significant. Turning to the incidence of short gestation, we again find the third trimester has the biggest effect, but the first and second also appear significantly related to short gestation.

4.3. Monetary evaluation

To value the impact of recent declines in SO2 from the strikes, we perform the following illustrative calculations, similar to Currie et al. (2009). To value the improvements in birth weight, we compute the percentage change in birth weight from the change in pollution in October 2010 by dividing the estimated impact of third-trimester SO2 on birth weight from table 4 (140) by the mean birth weight in our sample (3220) from table 1. We multiply this by the estimated elasticity between birth weight and earnings of 0.1 from Black et al. (2007) to obtain the percentage change in earnings during the month of strikes. We also multiply this by the average gross annual earnings of all full time workers (2764 euros, multiplied by 12) from the Directorate for Research, Studies, and Statistics DARES in 2010 in France. We finally multiply by the total number of births in 2010 (832,799) from INSEE to get the change in earnings per year. This gives an estimated increase in nationwide earnings of 120 million euros. Assuming a 40 year working career with 3 percent annual rise in earnings and a 6 percent discount rate, this amounts to 2.933 billion euros per cohort. If we attribute all of the estimated 15 unit decline in SO2 was due to the strike, this implies that a 1 unit decrease in SO2 increases future earnings of a given birth cohort by 196 million euros per year.[4]

6. Conclusion

The goal of this paper was to estimate the health externality from energy production, focusing on birth outcomes for those exposed prenatally. To account for the endogeneity of pollution exposure, we exploit the oil refinery strike that occurred in October 2010, which led to a sharp, temporary reduction in SO2 in areas close to the refineries. This reduction led to a robust increase in birth weight and gestation of infants, particularly those who were exposed during their third trimester of pregnancy. Our estimates suggest that the externalities from oil production that accrue to newborns alone are quite sizeable and should be an important part of policy discussions surrounding the production of energy.

[4] Clearly, these estimates understate the full benefits from a decrease in SO2 because they only capture the earnings impacts for a birth cohort and only capture the effects on births.

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Figure 1: Adjusted SO_2 levels by area

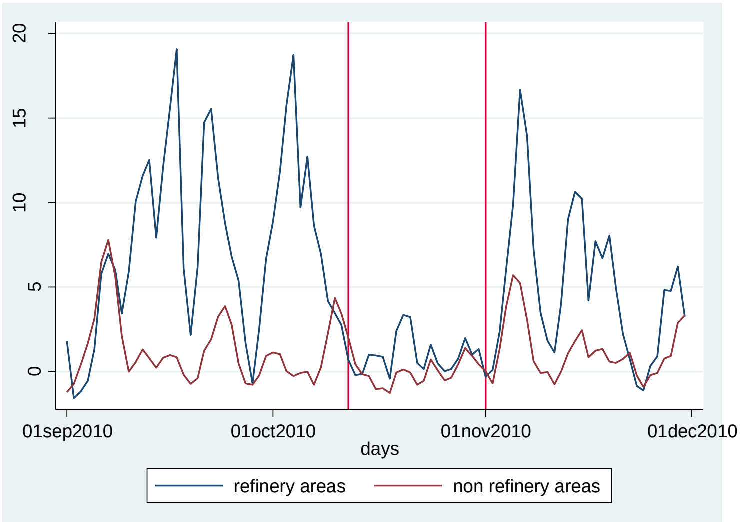

Figure 2: Birth weight distribution

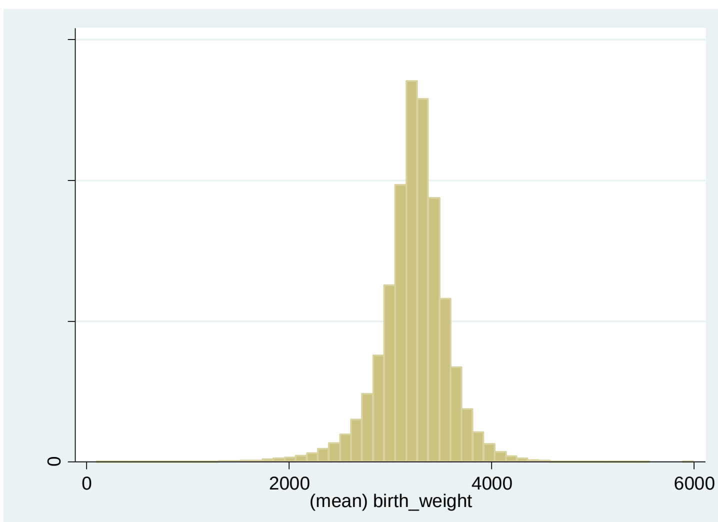

Figure 3: Unemployment distribution

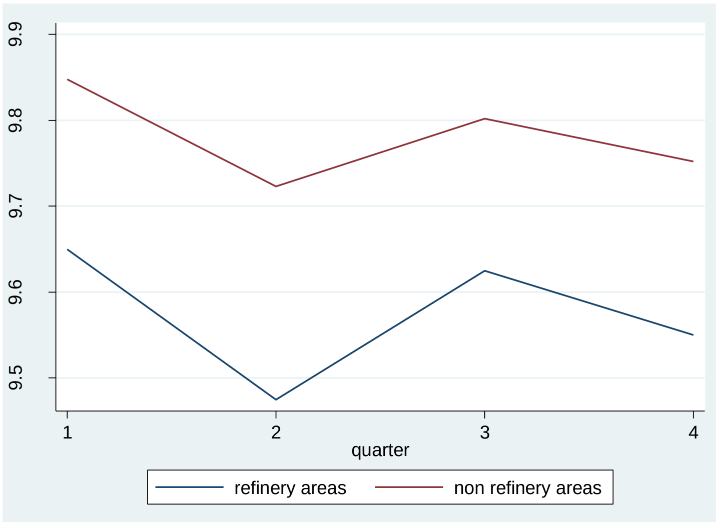

Figure 4: Adjusted Benzene, NO_2, and PM_{10} by area

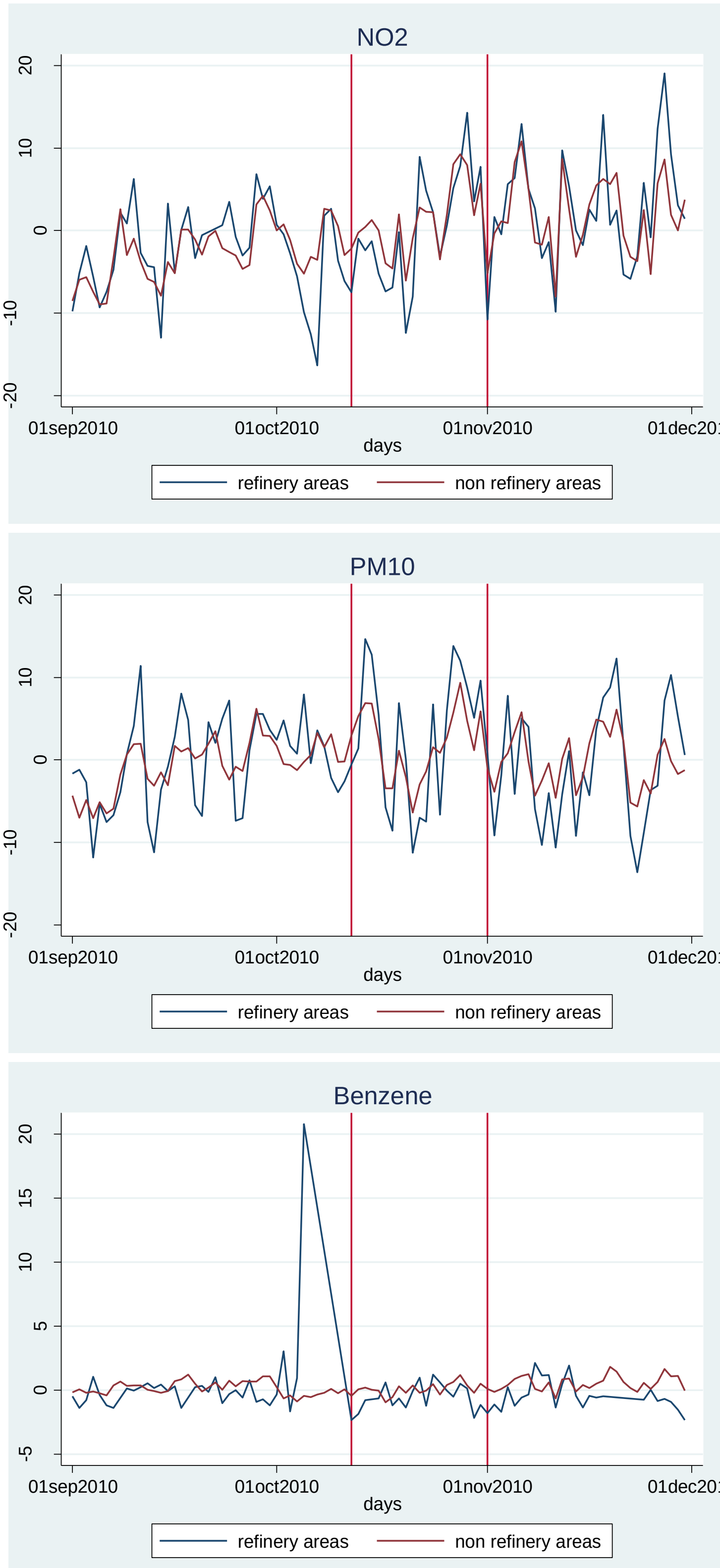

Figure 5: Monitoring stations in France

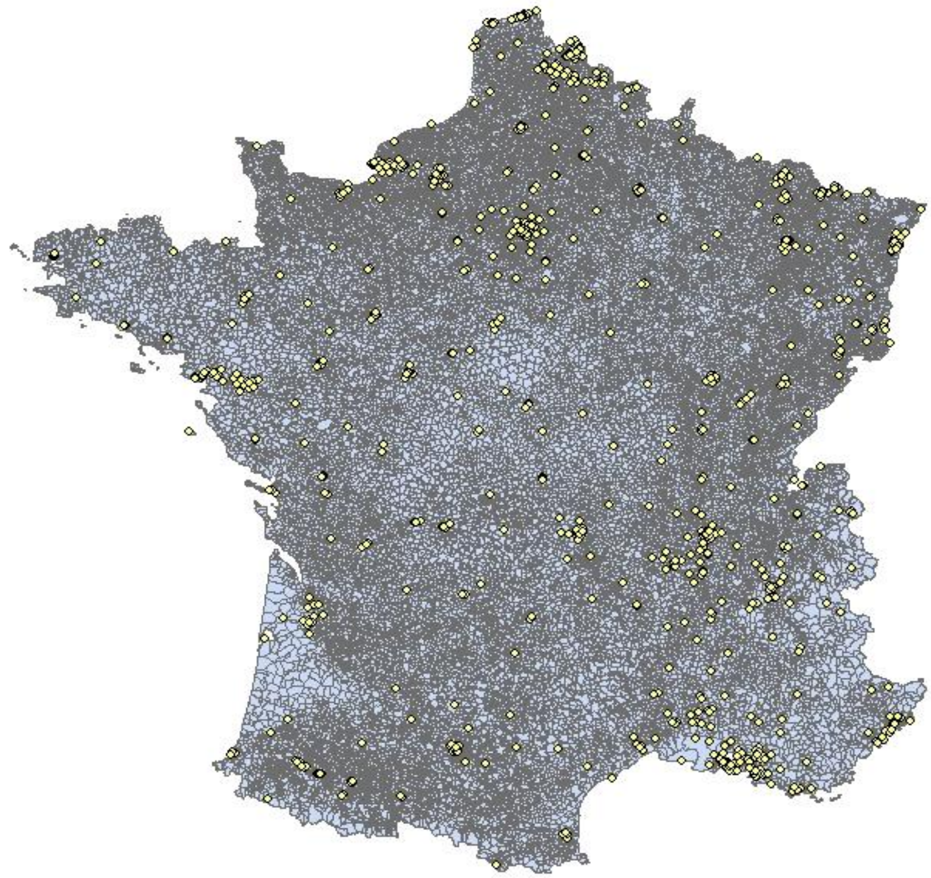

Table 1: Summary statistics

	All mean [SD]	Treatment group (all time periods) mean [SD]	Control group (all time periods) mean [SD]
Panel A			
birth weight (grams)	3227.65 [353.48]	3220.18 [271.56]	3227.66 [353.52]
birth weight <2500g	.0311 [.17]	.02 [.13]	.03 [.17]
gestational age (weeks)	38.86 [1.50]	38.78 [1.31]	38.86 [1.50]
gestational age <37w	.08 [.27]	.08 [.27]	.08 [.27]
Panel B			
SO2 - monthly average	3.82 [4.53]	12.87[10.86]	3.63 [4.098]
SO2 - # of exceedances of AQS (24 hours: 0.04 ppm (105 µg/m3))	138.99 [41.99]	134.62 [34.07]	140.49 [44.33]
NO2 - monthly average	24.22 [14.81]	23.35 [12.27]	24.23 [14.83]
PM10 - monthly average	22.55[7.45]	22.52 [6.76]	22.56[7.45]
PM10 - # of exceedances of AQS (24 hours: 50 µg/m3))	63.85 [14.70]	66.04 [17.64]	63.83 [14.68]
Benzene - monthly average	2.07 [3.91]	3.20 [2.07]	2.01 [4]
Panel C			
mean temperature (^{0}C)	11.856 [5.91]	11.74 [5.652887]	11.86 [5.92]
max. temperature(^{0}C)	16.57 [6.76]	16.34 [6.551971]	16.57[6.76]
Precipitation (mm)	2.19[1.44]	2.28 [1.30	2.19 [1.44]
wind speed (m /sec)	6.94 [1.45]	6.96 [.97]	6.95 [1.45]
wind direction (wind rose)	208.381[40.44]	205.77 [38.14]	208.39[40.44]
min. humidity (%)	55.07 [12.03]	56.32[12.50]	55.07[12.03]
max. humidity (%)	92.68[4.13]	93.19 [4.02]	92.6[4.13]
Panel D			
unemployment rate	8.71[2.22]	8.50 [1.10]	8.71[2.22]

Table 2: The effect of the strike on SO_2 levels

	1	2	3
<u>1. All Insee codes</u>			
strike	-15.24*	-15.30*	-15.27*
	(8.796)	(8.799)	(8.772)
Observations	151,624	151,624	151,624
R-squared	0.758	0.758	0.758
<u>2. Insee codes < 8km from monitor</u>			
strike	-16.48*	-17.06*	-16.63*
	(9.020)	(9.065)	(8.713)
Observations	16,945	16,945	16,945
R-squared	0.757	0.758	0.758
<u>3. Insee codes < 2km from monitor</u>			
strike	26.49**	28.86**	-25.22**
	(11.23)	(11.30)	(10.79)
Observations	5,652	5,652	5,652
R-squared	0.756	0.757	0.757
Weather	n	y	y
Local economic conditions	n	n	y

Note: This table provides the coefficient estimates of the effect of strike on Sulfur Dioxide (SO2). All specifications include Insee code fixed effects, year and month dummy variables, with standard errors clustered at the month and department level in parenthesis. The weather variables include average and maximum temperature, precipitation, minimum and maximum humidity, wind speed and direction. The unemployment rate is our measure of local economic conditions. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1

Table 3: The effect of the strike on birth weight and gestational age over the entire pregnancy

	BW			BW<2500g		
	1	2	3	4	5	6
1. All Insee codes						
strike	73.61*	76.47*	76.44*	-0.0204*	-0.0214*	-0.0214*
	(44.61)	(44.75)	(44.73)	(0.0109)	(0.0109)	(0.0109)
Observations	121,157	121,157	121,157	121,157	121,157	121,157
R-squared	0.053	0.053	0.053	0.066	0.066	0.066
2. Insee codes <8km from a monitor						
strike	71.87	74.87*	74.03*	-0.0191*	-0.0196*	-0.0193*
	(44.50)	(44.91)	(44.83)	(0.0112)	(0.0115)	(0.0115)
Observations	14,169	14,169	14,169	14,169	14,169	14,169
R-squared	0.043	0.044	0.045	0.066	0.067	0.067
3. Insee codes <2km from a monitor						
strike	92.38*	99.43**	99.03**	-0.0251*	-0.0263*	-0.0260*
	(47.21)	(48.41)	(48.41)	(0.0136)	(0.0141)	(0.0142)
Observations	4,962	4,962	4,962	4,962	4,962	4,962
R-squared	0.055	0.059	0.060	0.049	0.054	0.054

	Gest			Gest<37wks		
	1	2	3	4	5	6
1. All Insee codes						
strike	0.361*	0.382*	0.383*	-0.0905***	-0.0935***	-0.0937***
	(0.194)	(0.196)	(0.195)	(0.0294)	(0.0292)	(0.0292)
Observations	90,134	90,134	90,134	90,134	90,134	90,134
R-squared	0.071	0.071	0.071	0.075	0.075	0.075
2. Insee codes <8km from a monitor						
strike	0.366*	0.373*	0.373*	-0.0877***	-0.0867***	-0.0867***
	(0.196)	(0.197)	(0.197)	(0.0298)	(0.0297)	(0.0297)
Observations	10,761	10,761	10,761	10,761	10,761	10,761
R-squared	0.081	0.083	0.083	0.087	0.089	0.089
3. Insee codes <2km from a monitor						
strike	0.375	0.407*	0.400*	-0.0623*	-0.0658*	-0.0647*
	(0.243)	(0.242)	(0.241)	(0.0372)	(0.0363)	(0.0362)
Observations	3,849	3,849	3,849	3,849	3,849	3,849
Weather	n	y	y	n	y	y
Local economic conditions	n	n	y	n	n	y

Note: Note: This table provides the coefficient estimates of the effect of strike on birth weight and gestational age by trimester of pregnancy. All specifications include INSEE code fixed effects, year and month dummy variables, with standard errors clustered at the month and department level in parenthesis. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1

Table 4: The effect of the strike on birth weight and gestational age by trimester of pregnancy, distance<8km

	BW			BW < 2500g		
	1	2	3	4	5	6
strike - 3rd trimester	139.3***	150.3***	151.2***	-0.0225**	-0.0241**	-0.0244**
	(48.65)	(50.01)	(50.15)	(0.0112)	(0.0121)	(0.0122)
strike - 2nd trimester	5.252	9.235	10.63	-0.0179	-0.0180	-0.0185
	(67.12)	(66.63)	(66.14)	(0.0116)	(0.0121)	(0.0122)
strike - 1st trimester	70.67	64.87	60.02	-0.0170	-0.0166	-0.0148
	(77.86)	(78.18)	(78.78)	(0.0118)	(0.0122)	(0.0120)
Observations	14,169	14,169	14,169	14,169	14,169	14,169
R-squared	0.043	0.044	0.045	0.066	0.067	0.067

	gest			gest<37wks		
	1	2	3	4	5	6
strike - 3rd trimester	0.796***	0.844***	0.847***	-0.101***	-0.110***	-0.110***
	(0.221)	(0.226)	(0.226)	(0.0300)	(0.0309)	(0.0310)
strike - 2nd trimester	0.122	0.128	0.133	-0.0836***	-0.0807***	-0.0814***
	(0.310)	(0.300)	(0.300)	(0.0296)	(0.0294)	(0.0295)
strike - 1st trimester	0.176	0.146	0.138	-0.0780**	-0.0695**	-0.0685**
	(0.245)	(0.250)	(0.250)	(0.0323)	(0.0331)	(0.0330)
Observations	10,761	10,761	10,761	10,761	10,761	10,761
Weather	n	y	y	n	y	y
Local economic conditions	n	n	y	n	n	y

Note: This table provides the coefficient estimates of the effect of strike on birth weight and gestational age by trimester of pregnancy when the distance from the INSEE code to the pollution monitor is less than eight kilometers. All specifications include INSEE code fixed effects, year and month dummy variables, with standard errors clustered at the month and department level in parenthesis. Statistical significance is denoted by: *** p<0.01, ** p<0.05, * p<0.1