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ABSTRACT

Air Pollution during Pregnancy and Birth Outcomes in Italy*

We investigate the impact of fetal exposure to air pollution on health outcomes at birth in Italy in the 2000s combining information on mother's residential location from birth certificates with information on PM10 concentrations from air quality monitors. The potential endogeneity deriving from differential pollution exposure is addressed by exploiting as-good-as-random variation in rainfall shocks as an instrumental variable for air pollution concentrations. Our results show that both average levels of PM10 and days above the hazard limit have detrimental effects on birth weight, duration of gestation as well as overall health status at birth. These effects are mainly driven by pollution exposure during the third trimester of pregnancy and further differ in size with respect to the maternal socio-economic status, suggesting that babies born to socially disadvantaged mothers are more vulnerable. Given the non negligible effects of pollution on birth outcomes, further policy efforts are needed to fully protect fetuses from the adverse effects of air pollution and to mitigate the environmental inequality of health at birth.

JEL Classification: I18, J13, Q53, Q58

Keywords: air pollution, particulate matter, birth weight, pre-term birth, environmental policies

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1 Introduction

Air pollution is a key environmental and social issue of our time that, to a different extent, affects all regions, age and socio-economic groups. This poses multiple challenges in terms of management and mitigation of harmful pollutants (Viard et al., 2015). Indeed, the policy efforts and costs faced so far to reduce air pollution have been substantial (Fenger, 2009; Guerreiro et al., 2014), with many countries experiencing cleaner air. Despite these efforts, the concentration levels still exceed the recommended limits in many cities, especially for particulate matter (PM) (EEA, 2016).

While the adverse health effects of air pollution in the adult population have been largely documented (Anderson, 2009), much less is known about the effects on infants and only few studies investigate the impacts of *in utero* exposure during pregnancy. Most contributions consider infant mortality as the main outcome, because of both high availability of mortality data on a large population scale and the relevance of infant mortality for policy development (Cesur et al., 2017, among others).[1] Only few of them focus on less severe health outcomes at birth, which have been demonstrated to be a good proxy for individual performance later in life (Black et al., 2007). Indeed, studying the impact of prenatal pollution exposure on fetal health is important because the intra-uterine environment is a crucial determinant of infant's survival and health for the years to come. Previous studies include pre-term birth (PTB) and low birth weight (LBW) among risk factors for delays in motor and social development throughout early childhood (Hediger et al., 2002). They also show that neonates with low birth weight who survive infancy are at increased risk for health problems and death from ischemic heart disease (Barker et al., 1989). Finally, birth weight (BW) strongly affects child cognitive development (Figlio et al., 2014), predicts important socio-economic outcomes later in life such as annual earnings (Bharadwaj et al., 2017) and is also subject to intergenerational transmission (Currie and Moretti, 2007). Given that health shocks can impact human capital covering labor supply, productivity, and cognition, air pollution can be viewed as an important factor of production associated with economic growth. In this respect, the negative effects of poor health at birth on future child and adult outcomes stress the importance to identify the risk factors for fetal development (Currie, 2009), among which exposure to PM is an important one. Nevertheless, the causal evidence on the impact of PM on health outcomes at birth remains scant.[2]

The present paper addresses this issue by examining the impact of air pollution on infant health in Italy in the 2000s. Our work offers several contributions over the existing literature. First, we analyze the case of Italy as its experience is certainly relevant to the current debate on the regulation of air pollution. Indeed, Italy's air pollution levels are relatively lower than the ones experienced in industrializing countries such as China or India, but still comparable

[1] The distinction between infant, neonatal, and fetal mortality relies on the time of death. Infant (neonatal) death occurs within the first year (month) after birth, while fetal death is registered if a child died before birth.

[2] Noteworthy is the work by Currie et al. (2009) who analyze the impact of carbon monoxide (CO), ozone (O3), and PM_{10} on birth outcomes, though the estimated effects for PM_{10} and O3 are much less robust than the ones for CO.

with those experienced by many other industrialized countries. This has important policy implications as, while the effects of air pollution matter even at relatively low concentration levels (Currie and Walker, 2011, among others), the policy costs required for cleaner air are increasing at the margin, with further reductions in pollutant concentrations being more and more costly (EEA, 2014). Second, we use a unique dataset which combines rich administrative data from the Italian national registry of births, data for PM_{10} concentrations at daily level obtained from monitoring stations, and granular weather information from reanalysis models. By exploiting precise alignment of high-frequency weather and air pollution data, we frame our analysis in a quasi-experimental framework, in which rainfall shocks are used as an instrumental variable for non-random air pollution exposure. We are thus among the few to provide the causal impact of PM_{10} on a rich set of health outcomes at birth, analyzing both the entire pregnancy period and each trimester separately. Finally, while previous research mainly focused on birth weight and gestation as proxies for health at birth, we extend the analysis to a broad range of birth outcomes including intra-uterine growth retardation (IUGR) and Apgar index (APGAR). In addition to consider the absolute PM_{10} concentration as a risk factor for fetal health, we investigate the effects of number of days of prenatal exposure to pollution levels beyond the recommended limit, a treatment which has been overlooked in the literature on birth outcomes so far.

Our results show that both pollution exposure measures have significant negative effects on all fetal health outcomes under study. In particular, we find statistically significant adverse effects on weight, gestational age, pre-term birth as well as overall health status of the newborn, ceteris paribus. A trimester-specific analysis reveals that exposure in the third trimester is mostly the driving gestation window responsible for detrimental birth outcomes. Our empirical findings are robust to a set of sensitivity and robustness tests, which provide support to the causal interpretation of the estimated effects.

The reminder of the paper is as follows. Section 2 describes the relationship between air pollution and human health and provides a brief review of the empirical findings. Section 3 presents the data employed and some descriptive evidence, while Section 4 illustrates the identification strategy and estimation method. Section 5 reports the results, offering a comparison to other studies. Section 6 analyzes the treatment effect heterogeneity and explores the robustness of our findings. In Section 7 we discuss the limitations of our study. Section 8 offers some policy implications of our findings.

2 Background

Air pollution is characterized by high spatial and temporal variability. It includes a large number of substances either directly emitted into the atmosphere such as particulate matter (PM), carbon monoxide (CO), sulphur dioxide (SO_2), and nitrogen dioxide (NO_2) or formed from chemical reactions in the presence of other pollutants such as ozone (O_3) (EEA, 2016). In this study we focus on PM_{10}, a particulate matter with less than 10 micrometers (µm) in aerodynamic diameter, which is considered one of the most serious hazards for human health at global level (WHO, 2013).[3] It originates from natural sources such as volcanic ash and naturally suspended dust as well as from anthropogenic sources such as fuel combustion in thermal power generation, domestic heating for households, and fuel combustion for vehicles (EEA, 2016).

The adverse health effects of PM_{10} depend on the concentration and duration of exposure as well as particles' deposition. Long-term exposure, possibly to high pollution levels, is likely to produce larger, more persistent and cumulative effects than short-term exposure. Further, the deeper the particles are deposited, the longer it takes to remove them from the human body. While there is general consensus on the mechanisms behind the health responses to fine particle inhalation among adults (Xu et al., 2014), the biological pathway through which prenatal exposure to PM affects fetal health is more controversial. The dominant explanation is that maternal exposure to air pollution during pregnancy can affect fetuses because of its effect on maternal health. Inhaled fine particles that enter through the nose and throat can easily penetrate deep into the lungs and blood streams unfiltered. The processes responsible for adverse health at birth are related to inflammation, oxidative stress, endocrine disruption, and insufficient oxygen transport across the placenta, to which the immature fetal cardiovascular and respiratory systems are particularly sensitive (Whyatt and Perera, 1995).[4] The resulting fetal exposure can increase the risk of pre-term birth (PTB), low birth weight (LBW) or very low birth weight (VLBW), linked to shortened length of gestation (GEST) and/or intra-uterine growth restriction (IUGR).

The adverse health effects of extreme pollution events are well established in the epidemiological literature. One of the most famous studies looked at the London Great Smog and found dramatic increases in cardiopulmonary mortality (Logan, 1953). Later studies have investigated the link between moderate pollution and health, suggesting negative associations between pollution and infant health. Some studies have also provided evidence of critical windows of fetal exposure. In this respect, the most vulnerable gestation period varies with respect to the birth outcome considered. For example, maternal exposure to PM_{10} during early or mid-pregnancy is harmful to fetal health in terms of lower birth weight and increased risk of low birth weight (Lee et al., 2003), while the most critical pregnancy window for premature birth is the third trimester (Balsa et al., 2016). Finally, the risk of pre-term birth also increases in response to PM_{10} exposure six weeks and even two or five days before birth (Sagiv et al., 2005).

An important limitation of these studies is that they do not allow for a causal interpretation of the results. Capturing the causal effects of prenatal air pollution on health at birth is challenging because maternal exposure to pollution is likely to be non-random and systematically correlated with other determinants of birth outcomes. Ignoring these factors might lead to compute biased estimates.

[3] Particulate matter embraces particles of different sizes and compositions. $PM_{2.5}$ represents a further major particle pollutant with an aerodynamic diameter smaller than 2.5 micrometers.

[4] Epidemiological research suggests that a potential mechanism responsible for the association between prenatal air pollution and fetal health is a decline in the mitochondrial content of the placenta essential to the nourishment, growth, and development of the fetus. For a review of epidemiological literature on this topic, see Barrett (2016).

Several economic studies have addressed the non-random assignment of pollution relying on comparisons across siblings in a panel framework, showing that the estimates from a pure cross-sectional analysis tend to be larger in magnitude. Currie et al. (2009) investigate the impact of air pollution on infant health, measured by birth weight, length of gestation, and mortality in New Jersey during the 1990s. The authors address the issue of geographical sorting (of non-movers) and all other time-invariant maternal characteristics that can introduce endogeneity in the exposure by means of mother fixed effects. They report strong evidence of significant effects for CO on health at birth, and to a lesser extent also for PM_{10} and O_3. Following a similar strategy based on mother fixed effects, Currie and Schwandt (2016) investigate the impact of fetal exposure to toxic dust and smoke released into the air of lower Manhattan resulting from the collapse of the World Trade Center in New York in Sept.11th, 2001. The authors show that residence in the affected area increased PTB and LBW, especially for boys.

A related strand of the literature has investigated the causal effect of pollution on birth outcomes by exploiting exogenous shocks in air quality as natural experiments such as economic recessions, environmental disasters, regulations of allowed pollution levels, implementation of congestion tax or other policy changes. Currie and Walker (2011) study the impact of sharp reductions in local traffic congestion and the related air emissions caused by the introduction of electronic toll collection (E-ZPass) on health of infants born from mothers in residential proximity to toll plazas. They find that E-ZPass reduced NO_2 levels, with a lower incidence of PTB and LBW in the proximity of toll plazas. Oil refinery strikes in France served as a natural experiment to analyze the effects of pollution on health at birth in a study by Lavaine and Neidell (2017), which shows that the temporary disruption in the processing of oil led to significant declines in SO_2 concentrations and increases in birth weight and length of gestation of the newborns. The strongest effects are observed for exposures to the strike during the first and third trimesters of pregnancy. The impact of emissions from energy sources on birth outcomes has also been studied in Yang et al. (2017). The authors use direction-adjusted SO_2 emissions from a coal-fired power plant in Pennsylvania to instrument for SO_2 concentrations in New Jersey, finding that prenatal exposure to SO_2 increases the risk of LBW and VLBW. Chay and Greenstone (2003) exploit geographic variation in pollution shocks induced by a recession in 1981-1982 in the US to identify the causal effect of total suspended particulates (TSPs) on infant mortality. Their findings suggest that the incidence of LBW decreased in response to declines in TSPs. Reductions in TSPs, in turn, led to fewer deaths, largely occurring during the neonatal period, which points to weak fetal development via maternal exposure as an important pathophysiologic mechanism (see also Knittel et al. (2016) for air pollution effects on infant mortality and the associated mechanisms). Recently, Simeonova et al. (2018) have examined the effects of implementing a congestion tax in central Stockholm on both ambient air pollution and local children health. They find that the tax reduced NO_2 and PM_{10} concentrations and that this reduction in air pollution was associated with a significant decrease in the rate of acute asthma attacks among young children.[5]

[5]More recently, a new wave of studies has examined the impact of pollution on other aspects of human life. Ebenstein et al. (2016) study the effect of elevated levels of $PM_{2.5}$ on student test scores of Israeli students;

3 Data

Our analysis file combines administrative data from the Standard Certificates of Live Births (SCLB) with ambient air pollution monitoring data from the European Air Quality Database (Airbase). This section describes the datasets and the sample selection.

3.1 Birth Data

The main dataset used in this study comes from the birth certificates (Standard Certificates of Live Births, henceforth SCLB) from the Italian Ministry of Health, collected on the entire population of mothers who delivered both in public and private hospitals between 2002 and 2008. The dataset amounts to about 3,400,000 observations overall. The SCLB is filled in within ten days after the delivery by one of the birth attendants (e.g., doctor, midwife) and provides information on newborns' and mothers' characteristics, among which the newborn's date of birth and the geographic residence of the mother at the municipality level.[6]

Additionally, the SCLB contains detailed information on hospital of delivery, sex of newborn, pluriparity, and presence of neonatal pediatrician at delivery, as well as several measures of infant health at birth. Background information on the mother includes demographic and labor market information, childbearing history and prenatal care. Unfortunately, the SCLB data do not allow to identify babies born to the same mother because the fiscal code of the mother is anonymized.

The main outcomes of interest are measures of gestation (GEST and PTB) and measures of weight at birth (BW, LBW, and VLBW). Gestational age (GEST) measures gestation duration in days;[7] pre-term birth (PTB) is coded as a dummy equal to one if a baby is born alive before 37 completed weeks of gestation and zero otherwise; BW measures birth weight in grams, while LBW and VLBW are coded as dummies equal to one if weight at birth is less than 1,500 and 2,500 grams, respectively, and zero otherwise. Additionally, we employ IUGR as an outcome, coded as a dummy equal to one if reduced fetal growth for a given gestational age has been diagnosed and zero otherwise. Finally, we use the Apgar score measured five minutes after birth to construct a dummy equal to one if the Apgar score is less than nine and zero otherwise.[8]

Sager (2016) documents the existence of a relationship between pollution and road safety in the UK; Lichter et al. (2017) show that variation in pollution affects professional soccer players in Germany. Finally, Isen et al. (2017) find a significant relationship between pollution exposure in the year of birth and later-life outcomes such as labor force participation and earnings at age 30, using the Clean Air Act as a source of exogenous variation in TSPs.

[6] In Italy, municipality is the finest administrative unit, with an average area of only 22 km^2. The Italian geographical administrative system is organized in regions, provinces and municipalities corresponding, respectively, to the NUTS-2, NUTS-3 and NUTS-4 Eurostat regional breakdown.

[7] Gestational age refers to the length of pregnancy after the first day of the last menstrual period and is reported in weeks. The estimation of gestational age is generally based on the last menstrual period, ultrasound or physical examination, but birth certificates do not report the exact method. The date of onset of the last menstrual period serves as a proxy for the date of conception and is calculated by subtracting the number of gestation days from the birth date.

[8] The Apgar score is a summary measure of a newborn's physical condition based on appearance, pulse, grimace, activity, and respiration and determines need for special medical care. It ranges from zero to a maximum total score of ten and is a good predictor of survival and neurological problems at one year of age

We restrict our sample to mothers aged between 15 and 45. Then, we consider only singleton births and newborns with gestational age between 26 (who have completed the second term of pregnancy) and 44 weeks and birth weight between 500 and 6,500 grams. We drop missing values in the relevant variables and year 2002 due to an insufficient number of installed stations monitoring PM_{10} concentration levels (see next section for details on this point). These restrictions reduce our sample to 2,626,381 observations. We collapse birth data by mother's municipality of residence $\times$ week of child's birth to ease the computational burden and to account for the identifying variation occuring at a higher level of aggregation. In fact, we do not know exact mothers' locations within municipalities and assume that mothers in each municipality are exposed to the same air pollution level. In this way, we obtain a sample of 860,473 municipality by week-of-birth cells.

We finally add information on the average gross income per capita in the municipality of mother's residence as a proxy for income, obtained from the Ministry of Interior and based on the individuals' declarations as reported to the Italian Revenue Agency (Agenzia delle Entrate).

3.2 Environmental Data

We measure air pollution using data from the European Air Quality Database (Airbase), which collects information on 24h average of PM_{10} concentrations, corresponding to national ambient air quality standards, registered by monitoring stations.[9] The number of monitoring stations does not cover the whole Italian territory and varies across space and time, as some municipalities have installed stations after the introduction of more stringent regulation on air quality. Moreover, few of them operate continuously. Given concerns about the endogeneity of monitor "births" and "deaths" (Bharadwaj et al., 2017), we use data only from monitors that have more than 90% of readings in the period of study. We exclude year 2002 because there were too few monitoring stations and the constraint on the minimum number of readings over the period would have greatly reduced the number of municipalities under study. This restriction leaves us with a sample of 109 monitoring stations with valid records from 2003 to 2008 for a total of 59 municipalities. In case a municipality comprises more than one monitoring station like in big cities, we impute to the municipality the average of pollution concentration levels registered in all the monitoring stations belonging to that municipality. Figure 1 shows the geographical distribution of the selected municipalities, mainly clustered in the North but some also present in the South and in the Islands. Moreover, for each municipality, we construct the average PM_{10} concentration by taking the mean of the daily PM_{10} values over the period of analysis. As evident from Figure 1, the municipalities in the North are more polluted than in the South and some of them show values close to the EU annual concentration limit of 40 mcg/m^3. Figure 2 plots weekly pollution levels for each

(Apgar, 1966). An Apgar score lower than nine is considered a critical threshold, below which the newborn's health might be compromised.

[9] The Airbase database is maintained by the European Environmental Agency (EEA) through the European topic center on Air Pollution and Climate Change mitigation. It contains air quality data delivered annually under the 97/101/EC Council Decision, establishing a reciprocal exchange of information and data from networks and individual stations measuring ambient air pollution within the member states.

municipality and shows that within municipality there is considerable variation in pollution levels over time. Figure 2 also plots residual pollution levels after controlling for time and municipality fixed effects and the weather variables included in our regression models. These plots show that after adjusting for these factors, there is still considerable variation left to identify the effect of pollution.

Because weather, particularly temperature, can potentially impact pollution formation as well as child health (Deschênes et al., 2009), we bring in data on temperature and precipitations obtained from the Directorate D - Sustainable resources/Unit 05 of the European Commission (Gridded Agro-Meteorological Data - CGMS). The CGMS database contains meteorological parameters from weather stations interpolated on a 25x25 km grid. They are available on a daily basis from 1975 and cover the whole Italian territory. Given that weather data are arranged in the form of a regular grid, to obtain homogenous measures at administrative level we assign the gridded values on a municipality-day basis through a spatial join by means of a Geographical Information System. From the CGMS data, we select the daily maximum and the daily minimum temperature, averaged over the entire pregnancy and expressed in Celsius degrees (°C), since temperature extremes are likely to be negatively perceived by mothers (Deschênes and Greenstone, 2011). In addition, we extrapolate the daily precipitation expressed in millimeters (mm) of rain.

As for the SCLB data, we collapse the environmental data by municipality $\times$ week for a total of 15,445 cells (59 municipalities with monitoring stations by an average of about 262 weeks over the period 2003-2008).[10] Since we use concentration values directly reported by monitoring stations to measure air pollution, pregnant women not living next to monitoring stations might be exposed to pollution levels other than those actually registered by the monitors, potentially generating a mismatch between the detected pollution level and the assigned one. However, we argue that it is unlikely to be a concern in our context because the geographical unit of analysis, i.e. the municipality, is extremely fine. This implies that although the exact mother's address is not available, this feature of the data allows us to minimize the measurement error when matching mothers with pollution data.

Finally, the birth data are matched with the environmental data, which leads to a final sample of 12,260 cells (54 municipalities x 227 weeks, on average). Therefore, each cell is made of mothers who live in the same municipality and give birth in the same week of the year.

3.3 Descriptive Statistics

Summary statistics of the baseline sample are presented in Table 1. Panel A of Table 1 shows the summary statistics for the birth outcomes, which by and large depict a healthy newborn population, with an average BW of almost 3.3 kg, in line with the main international clinical standards (WHO, 2006). Good health at birth is also reflected in a small portion (only 3%) of newborns with low Apgar score (APGAR), as well as GEST (273 days corresponding to

[10] Given the unbalanced nature of monitoring stations data, we do not have always the same number of weeks across municipalities.

39 weeks of gestation, on average). The prevalence for LBW is 5%, for VLBW is 1%, for IUGR is 2%, and for PTB is about 5%.

Looking at the pollution variables in Panel B of Table 1, we observe that the mean PM_{10} concentration level during the whole pregnancy is almost 35 mcg/m^3. The number of days with PM_{10} concentration levels above the limit is about 54 days during pregnancy. This means that any mother in our sample experienced on average more than once per week off-limit days during her pregnancy, and many of them experienced high PM_{10} concentration levels several times.

Panel C of Table 1 reports the summary statistics for the main covariates. As covariates we include child's sex at birth (female=1), neonatal pediatrician at delivery (present, absent or missing), type of hospital of delivery (private, public or missing), maternal age, a dummy for mother foreign born, a dummy for previous abortions including voluntary interruptions of pregnancy as well as miscarriages, a dummy for previous deliveries, a dummy for mother employed, maternal professional position (housewife, self-employed, dependent employee), maternal education (less than high school, high school, more than high school), and a dummy for married. Our sample of newborns is gender-balanced with a female share of about 49%. On average, mothers deliver between 32 and 33 years old. A preliminary look at the socio-economic traits reveals that about 26% of mothers have more than a high school diploma, 44% have a high school diploma and 30% don't have a diploma. Moreover, 68% are regularly employed; 56% are dependent employees, 10% are self-employed and 34% are housewives. As for the marital status, 73% of mothers are married, and 19% are foreign. The vast majority of mothers choose a public hospital (91%) and only 7% of mothers choose a private one. In 58% of the cases, there is a neonatal pediatrician at delivery. About 20% of mothers have experienced a previous abortion and about 45% already have children. The average gross income aggregated at the municipality level is slightly less than 24,000 measured in Euros constant at 2005.[11]

Panel D of Table 1 shows the summary statistics for the environmental variables: the average maximum and minimum temperatures during pregnancy amount to about 19 °C and 9 °C, respectively while the average cumulated rainfall during pregnancy is almost 600 mm. Figure 3 provides more details on the rainfall distribution. To this end, we show cumulated precipitations by year and week-of-year as well as the total number of rainy days by week-of-year and per week by municipality. It turns out that in years 2003 and 2008 it rained the most (Panel A), while autumn and winter were the most rainy seasons (Panel B). With respect to the rainfall frequency throughout the year, we do not detect any spikes in precipitations' variation (Panel C and Panel D). For example, the total number of rainy days per week ranged from almost 4 at the end of February to less than 1 in August (Panel C), and from slightly above 1.5 days in the municipality of Saliceto in the North-West of Italy to 3 days in Rovereto located in the North-East (Panel D).

Although our baseline sample represents only a small fraction of the birth population (about

[11] At the national level, the average income is 18,138.49 Euros (constant at 2005). The difference between the average income in our sample and the population average is due to the fact that the municipalities under study mainly belong to the richer North of Italy.

13%), we believe that this restriction does not introduce a sample selection. Table A1 in the Appendix provides a comparison of the two samples (before and after the matching with the environmental data) based on the outcomes means and some selected covariates. From the comparison between column 1 (estimation sample) and column 3 (full sample after restriction) it emerges that the baseline sample does not substantially differ from the total birth population and it is plausibly not affected by selection. The only notable differences are in the fraction of foreign, highly educated and employed mothers, which is higher in the estimation sample than in the full sample. This is probably due to the fact that most of the selected municipalities are located in the North of Italy, where many foreign people are located and female employment is higher.

Finally, following a standard methodology (Bharadwaj et al., 2017; Currie et al., 2009), we extend our sample to include municipalities whose centroid falls within a radius of 15 km from the monitors' geographical coordinates. This procedure allows us to expand the sample coverage to 1,029 municipalities and 13,143 municipality $\times$ week-of-birth cells, which we employ to perform robustness checks. Comparison between column 1 (estimation sample) and column 5 (extended sample) in Appendix Table A1 does not reveal any noteworthy difference in terms of observable characteristics.

4 Econometric Specification

4.1 Baseline Model

To investigate the relationship between *in utero* exposure to PM_{10} and birth outcomes, we first estimate the following fixed effects model:

$$Y_{mt} = \beta PM_{10,mt} + \mathbf{X}'_{mt}\delta + \mathbf{W}'_{mt}\lambda + \gamma I_{my} + \mu_m + \theta_t + \upsilon_{mt} \tag{1}$$

where Y_{mt} is one of the seven outcomes of interest (listed in Section 3.1) for mothers giving birth in municipality m during week-of-year t; $PM_{10,mt}$ denotes i) the average PM_{10} concentration level expressed in mcg/m^3 or ii) the number of days with PM_{10} concentration levels above the limit over the pregnancy; $\mathbf{X}_{mt}$ is a vector of mother- and child-specific characteristics (listed in Section 3.1) in the municipality-week-of-birth cell, which may also influence birth outcomes. We explicitly control for the average maximum and minimum temperatures in the municipality-week-of-birth cell denoted by $\mathbf{W}_{mt}$. I_{my} is the average per capita income at the municipality level in year y expressed in 2005 constant Euro. It serves as a proxy for maternal living conditions, which are likely to be correlated with both air quality and health at birth. μ_m are municipality fixed effects that control for time-invariant, unobserved determinants of birth outcomes for mothers living in a particular municipality m. θ_t are week-of-birth fixed effects to account for any periodic co-movements between pollution and birth outcomes as well as trends over time, such as improvements in healthcare. Finally, υ_{mt} is an idiosyncratic error component.

We cluster the standard errors at the municipality level, allowing for any spatial dependence of pollution exposure within the same municipality, and use as weights the number of births in each municipality-year. In this specification, we compare outcomes of children born in the same municipality during the same week. Hence, the identification comes from the residual variation within municipality-week-of-birth in PM_{10} exposure after controlling for climatic and temporal variability as well as predetermined mothers' and newborns' characteristics. The coefficient of interest is β, which captures the effect of i) one additional unit in the average PM_{10} concentration level during pregnancy or ii) one additional day with PM_{10} concentration level above the limit during pregnancy on birth outcomes for mothers living in a certain municipality m and giving birth in a given week-of-birth t, holding constant all the other variables listed in equation (1).

We also estimate a trimester-specific model to test whether the estimated effects are driven by a particular period of gestation, such as the first trimester when organsâ formation takes place and the fetus may be extremely sensitive to environmental conditions, or the third trimester during which fetuses generally gain weight. Thus, we estimate the following model:

$$Y_{mt} = \sum_{k=1}^{3} \beta_k PM_{10,k,mt} + \mathbf{X}'_{mt}\delta + \sum_{k=1}^{3} \mathbf{W}'_{k,mt}\lambda_k + \gamma I_{my} + \mu_m + \theta_t + \upsilon_{mt} \tag{2}$$

where $PM_{10,k,mt}$ denotes i) the average PM_{10} concentration level expressed in mcg/m^3 during trimester of pregnancy $k = 1, 2, 3$ or ii) the number of days during trimester of pregnancy $k = 1, 2, 3$ with PM_{10} concentration levels above the limit for mothers giving birth in municipality m at week t. $\mathbf{W}_{k,mt}$ measures the averaged maximum and minimum temperatures for each trimester k for mothers giving birth in municipality m at week t. β_k captures the effect of interest for trimester $k = 1, 2, 3$.

Maternal exposure to PM_{10} during pregnancy is likely to be correlated with many observable and unobservable determinants of fetal development and ultimately birth outcomes. Including municipality fixed effects in μ_m will absorb any time-invariant determinants of long-run characteristics unique to a specific municipality, while including week-of-birth fixed effects θ_t will control for short- and long-run time trends-driven determinants of birth outcomes common to all deliveries in a specific week of each year. Thus, in this baseline setup a causal interpretation of the effects would rely on the assumption that birth outcomes are not correlated with any unobserved maternal and municipality characteristics.

Given the cross-sectional nature of our birth certificates data, we cannot rule out the existence of time-varying unobservable characteristics that are correlated with both air pollution levels and birth outcomes. For instance, there may exist local and transitory determinants of health at birth that also covary with air pollution. Residential sorting arising from family wealth, heterogeneity in preferences for air quality, living conditions, access to medical care and other local amenities hints at endogeneity in maternal exposure to air pollution during pregnancy (Chay and Greenstone, 2005). These geographical differences in ambient pollution levels may be correlated with family characteristics that, in turn, may be correlated with other determinants of fetal health. On one side, air pollution generally tends to be lower in areas where families are wealthier, and wealthier people are likely to have access to higher quality healthcare, resulting in better health outcomes at birth. In this case, there would be a negative correlation between air quality and the error term υ_{itm}, thus introducing an upward bias in the OLS estimates of the parameter of interest relative to the true causal effect (Currie, 2011). On the other side, local economic activity may correlate with both air pollution and health at birth as well as fertility decisions (Dehejia and Lleras-Muney, 2004, among others), pointing again to endogenous fetal exposure. In this case, an economic expansion is likely to increase pollution concentration but also to correlate with higher income levels and/or better healthcare facilities. As a result, there would be a positive correlation between air quality and error term υ_{itm}, which would bias the OLS estimates downward (Knittel et al., 2016). As a matter of fact, any unobserved transitory local shocks that covary with both air pollution concentrations and fetal health will bias the OLS estimates of β (β_k).

4.2 Instrumental Variable Model

In order to address concerns about the endogeneity of pollution exposure, we exploit the as-good-as-random variation in local weather conditions, which are able to amplify or mitigate air pollution concentrations. Indeed, stable weather conditions along with intense local economic activity can keep concentration levels above the limit for several days, while for instance on windy days air pollution can be effectively dispersed far away from where it is locally produced. Previous studies have successfully employed weather conditions, in most cases wind, to instrument for air pollution. Yang et al. (2017) uses wind-direction-adjusted SO_2 emissions from a coal-fired power plant located in Pennsylvania as an instrument for SO_2 concentrations in New Jersey. Similarly, Anderson (2015) uses quasi-random variation in ultra-fine particles, nitrogen oxides, and CO generated by wind patterns near major highways. A bunch of local weather conditions has been likewise employed to instrument for PM_{10} and CO in Knittel et al. (2016), while Arceo et al. (2016) exploit thermal inversions, which are likely to lead to a temporary accumulation of certain types of pollutants, to instrument for PM_{10}, CO, SO_2, and O_3. Finally, Schlenker and Walker (2015) account for the fact that wind speed and wind direction transport air pollutants in different ways, using interactions between taxi time, wind speed, and wind angle from airports in California to identify the specific effect of CO and NO_2.

Building on these studies and on the evidence presented in Figure 4, we rely on quasi-experimental variation in PM_{10} exposure induced by rainfall shocks during pregnancy to identify the causal effect of pollution on birth outcomes. Recent findings in atmospheric chemistry have shown that rainfall fluctuations are able to affect pollution dispersion and accumulation (Yoo et al., 2014), and even small amounts of rainfall can have strong effects on PM concentrations (Ouyang et al., 2015). Due to its chemical composition, PM strongly depends on atmospheric conditions and in some scenarios an even stronger dependence on meteorological conditions than on anthropogenic emissions is possible (Barmpadimos et al., 2011; Wang et al., 2015). For example, He et al. (2017) find that meteorological conditions are the primary factor driving the day-to-day variations in pollutant concentrations (PM_{10} among others), explaining more than 70% of the variance of daily average concentrations in China.

The mechanism underlying the relationship between rainfall variation and local PM_{10} concentrations can be described as follows. The transportation of suspended particles from the earth's atmosphere to the ground occurs via dry and wet deposition processes. Wet deposition consists in removing particles from the atmosphere through precipitations such as rain, fog, and snow. As a raindrop falls through the atmosphere, it can attract numerous tiny aerosol particles to its surface before hitting the ground. The process by which droplets and aerosols attract particles is called coagulation, a natural phenomenon that can act to clear the air of particle pollutants such as PM_{10} (Ardon-Dryer et al., 2015). The effect of rainfall on pollution is broadly referred to as *wash-out* or *washing effect* (Guo et al., 2016). Figure 4 shows the monitor-level time series for PM_{10} pollution and precipitation over a period of six months (February-August) in 2006.[12] As expected, there is a well-defined negative association between daily pollution and daily precipitation: when it rains, the level of PM_{10} drops and viceversa.

We estimate equation (1) by 2SLS in a setup that includes the same set of socio-economic and demographic variables as well as fixed effects as reported in Table 2, using the cumulated precipitation level ($Rain_{mt}$) expressed in mm during pregnancy for mothers living in municipality m and giving birth in week t as an instrument for both i) the average PM_{10} concentration level during the pregnancy and ii) the number of days with PM_{10} concentration levels above the limit during the pregnancy.[13] When considering the two measures of PM_{10} concentration level in each trimester as in equation (2), the instruments are the cumulated precipitation levels ($Rain_{mt}$) expressed in mm during trimester $k = 1, 2, 3$, respectively, for mothers living in municipality m and giving birth in week t.

Our key identifying assumption is that fluctuations in rainfall do not directly affect health at birth through factors other than PM_{10} concentrations; or in other words, conditional on other covariates, the cumulative level of rainfall should not represent a risk nor a benefit per se for health at birth. Hence, our instrument should be uncorrelated with any other factors affecting birth outcomes, or more formally, $Cov(Rain_{mt}; \upsilon_{mt} | \mathbf{X}_{mt}) = 0$. This seems a plausible assumption once we control for municipality and week-of-birth fixed effects, temperature and mother's characteristics. In section 5.2.2, we present some evidence that the instrument is likely to satisfy the exclusion restriction required for a consistent estimate of β and β_k. While the identifying assumption is inherently untestable, we address potential concerns that could threaten the validity of the instrument via indirect tests. We also provide evidence that our estimates do not suffer from a weak instrument problem.

[12]The choice of this particular time window is only to improve exposition. The patterns, not shown here, are very similar for other time periods.

[13]We have also considered the average precipitation during pregnancy as a possible instrument for the average PM_{10} concentration level with very similar results. Additionally, we have used the number of rainy days as an instrument for the number of days with PM_{10} concentration levels above the limit but the instrument turned out to be weak.

5 Results

5.1 OLS Estimates

We begin by documenting the correlation between prenatal PM_{10} exposure during pregnancy and birth outcomes for each pollution measure adopted in this study. Table 2 presents the OLS estimates of β and β_k from equations (1) and (2), respectively, for our first measure of pollution exposure, i.e., the average PM_{10} exposure during pregnancy (Panel A) and in each trimester (Panel B).

[Table 2: about here]

The results in Panel A of Table 2 suggest that higher average PM_{10} values adversely affect fetal development during gestation for most of the birth outcomes under scrutiny. In particular, an increased PM_{10} concentration level significantly decreases the newborn's weight at birth (BW) as well as gestational length (GEST). Symmetrically, low birth weight (LBW), preterm birth (PTB), and low Apgar score (APGAR) significantly increase, while very low birth weight (VLBW) and intra-uterine growth restriction (IUGR) are unaffected by exposure during pregnancy.

A disaggregation of fetal exposure by trimester of gestation is presented in Panel B of Table 2. The trimester-specific analysis unveils an interesting pattern. It provides evidence that the most harmful effects of pollution exposure are at the early gestational stage, the so-called embryonic period, and at the late gestational stage, also known as prenatal period. Analogously to Panel A in Table 2, BW and GEST significantly decrease, while the incidence of LBW and PTB significantly increase, with the effects larger in the third trimester than in the first trimester of gestation. The effects for the second trimester are much smaller in size and not statistically significant. The results further indicate that exposure to PM_{10} during the third trimester also leads to an increased probability of low APGAR score and IUGR, though the latter effect is only weakly significant. Taken together, these findings suggest that the early and the late gestational periods might play a major role for fetal development *in utero*.

[Table 3: about here]

Table 3 presents the OLS estimates of β and β_k from equations (1) and (2) for the number of days with PM_{10} concentration level above the EU limit over the pregnancy (Panel A) and in each trimester (Panel B), respectively. The estimates for the whole gestational period and separately by trimesters broadly confirm the adverse effects of fetal exposure to particle pollution on birth outcomes obtained in Table 2. Indeed, ten additional days with PM_{10} concentration level above the EU limit during pregnancy (Panel A) significantly decreases the newborn's BW (-2.58 grams) and increases the predicted probability of LBW and PTB. Also for this pollution measure, trimester-specific contributions (Panel B) confirm the pattern, according to which fetal exposure in the early and late gestational periods is likely to be responsible for adverse health at birth, with the largest effects found during the third trimester of gestation. The effects for the second trimester are small in magnitude and in most cases not significant.

As discussed in section 4.1, the OLS regressions control for all time-invariant characteristics that may predict heath outcomes at birth. However, fixed effects regressions cannot control for all time-varying forms of endogeneity. For example, including municipality fixed effects will ignore time-varying determinants of birth outcomes unique to a specific municipality, for example economic conditions, improved hospital facilities or other local policies. Therefore, we turn to using rainfall fluctuations during pregnancy as a source of quasi-experimental variation to identify the causal effects of prenatal PM_{10} exposure on fetal health.

5.2 IV Estimates

5.2.1 Using Rainfall Variation in a Quasi-Experimental Design

We first present the first-stage relationship between rainfall variation and PM_{10} concentration levels.[14] Consistent with previous studies using weather conditions to instrument for pollution level (see Section 4.2), Table 4 shows a strong relationship between rainfall fluctuations and PM_{10} concentrations.

[Table 4: about here]

This relationship is robust across both measures of pollution exposure and gestation periods, suggesting that ten additional units in the cumulated precipitation level expressed in mm during the whole pregnancy decreases the average PM_{10} concentration level by about 0.16 mcg/m^3 (Panel A) and the number of days during pregnancy with PM_{10} concentration level above the EU limit by about 0.55 days (Panel B). Relative to a mean PM_{10} concentration level of 34.73 mcg/m^3 and a mean number of days with PM_{10} above the EU limit of 54.77 days during the entire gestational period, this corresponds to a 0.45% reduction in the average PM_{10} level and a 1.01% reduction in the number of days during pregnancy with PM_{10} above the EU limit for the average mother in our estimation sample.

When considering the first stage estimates by trimester, we use the three instruments (cumulated rainfall in I, II and III trimester) for each endogenous regressor. The point estimates on the diagonal in Table 4 show a significant negative effect, confirming that rainfall shocks in a trimester are a strong predictor of particulate pollution concentrations in the same trimester. Interestingly, the coefficients on rainfall precipitations one trimester backwards are often statistically significant as well, though much smaller in size. This evidence is in line with studies suggesting that the relationship between rainfall and atmospheric particle concentrations might be non-linear with a lag effect (Barmpadimos et al., 2011), implying that the *wash-out* effect is long-standing but potentially decreasing over time due to new local PM_{10} emissions

[14] We proxy rainfall variation during gestation by accumulated rain because in the meteorological literature rainfall precipitations are generally measured by cumulative rainfall carrying more information on the precipitations dynamics (Ouyang et al., 2015). Using average rainfall yields similar results though.

into the atmosphere. Finally, the F-statistics of excluded instruments are in general above the threshold of 10 as indicated in Staiger and Stock (1997), confirming that rainfall shock is not a weak instrument.[15] Overall the evidence shown in Table 4 supports the relevance of the instruments in our quasi-experimental setting.

A possible concern about the use of PM_{10} is that the sources of certain pollutants are similar and thus often vary jointly, which could make it difficult to establish which pollutant is responsible for adverse health effects. If the observed PM_{10} concentrations are correlated with other pollutants not considered in this study, then our estimates are likely to be upward biased, thus overestimating the true effects of PM_{10}.

[Figure 5: about here]

Figure 5 plots the correlations between PM_{10}, CO, NO_2, and SO_2, obtained from collapsed data at the weekly level and measured in standard deviations. The figure shows that PM_{10} is highly correlated with other pollutants, coming from many of the same sources, which might raise the question which pollutant drives the estimated results. However, we believe that this is not an issue in our context since our instrument allows to disentangle the effects deriving exclusively from particulate matter. Indeed, when testing the correlation between rain and other pollutants such as CO, NO_2, or SO_2, our instrument does not show any statistical power.[16] We interpret this result as a confirmation that the *wash-out* effect of rain applies exclusively to particulate pollution, which in turn indicates that variation in rainfall precipitations cannot be exploited to predict concentrations in other pollutants. These pieces of evidence reassure us that we are able to isolate the health effects at birth deriving only from variation in PM_{10} concentrations, induced by rainfall shocks.

Table 5 and Table 6 report the IV estimates of the effects of PM_{10} exposure on birth outcomes. Compared to the OLS estimates, the IV estimates are about two to four times as large and allow to unambiguously identify the most susceptible period of prenatal exposure.

[Table 5: about here]

Panel A of Table 5 reports the results for fetal exposure to the average PM_{10} levels during the entire gestational period. Birth outcomes based on weight (BW, LBW, VLBW) and gestational duration (GEST, PTB) are significantly affected by prenatal exposure to PM_{10}. In particular, ten additional units in the average PM_{10} concentration level would decrease BW by about 17.2 grams and GEST by almost 0.6 days, a reduction of about 0.5% and 0.2%, on average, respectively. Moreover, the same increase in PM_{10} concentration level would increase the probability of LBW, VLBW, and PTB by about 0.009, 0.002, and 0.01, respectively. For these outcomes, the proportional effects are larger, where a ten unit change in the mean PM_{10} would lead to an increase in the incidence of LBW by 18%, and in the incidence of VLBW and PTB by 20% each, on average. These greater effects suggest that

[15]The only exception is the F-statistics for average pollution during whole pregnancy in Panel A, which reports a value of 9.82.

[16]The results are available upon request.

newborns at risk of low and very low birth weight as well as premature birth are most likely to be affected by particulate pollution while *in utero*. Concerning the prevalence of IUGR and APGAR, we do not find a statistically significant relationship.

Panel B of Table 5 presents the IV estimates from the trimester-specific model, which suggests that the total effect observed for the entire pregnancy period mainly arises as a result of prenatal exposure during the last gestational period. In fact, the effects for the first and the second trimesters of gestation are much smaller in size and generally not statistically significant. More precisely, exposure to ten additional units in the average PM_{10} concentration level during the third trimester would significantly decrease BW by about 26.6 grams and increase the prevalence of LBW by about 0.017 and the prevalence of VLBW by about 0.003. These estimates suggest again greater proportional effects for the newborns at risk, implying a 0.8% reduction in BW and a much larger 34% (30%) increase in the incidence of LBW (VLBW), on average, in response to a ten units increase in the mean PM_{10} during the last trimester. Birth outcomes based on gestation, i.e. GEST and PTB, are statistically significantly affected alike. In fact, GEST would decrease by about 0.82 days, while PTB would increase by about 0.014. Finally, the newborn's overall health status would worsen as well, with an increased probability of having an Apgar score under nine (APGAR) by 0.038. In other words, a ten unit change in the mean PM_{10} during the third trimester is estimated to reduce gestation by 0.3%, increase the incidence of pre-term birth by 28% and that of low Apgar score by 12%, on average, pointing to a larger effect of PM_{10} for the newborns at risk of premature birth and bad overall health status at birth.

To compare the estimates for birth weight and gestation based on the trimester-specific contribution, we carry out the following calculation. Because fetus gains about 200 grams in weight per week in the final month of pregnancy (Cunningham et al., 2010), a 0.82-days reduction in gestation would translate into a reduction of 23.4 grams in weight, which is very close to our estimate of the impact on birth weight of 26.6 grams. Therefore, it appears that the reduction in birth weight in the third trimester arises solely due to shorter gestation, rather than to growth retardation. In support of this hypothesis, we do not find a statistically significant relationship between exposure to PM_{10} and IUGR. Taken together, the estimated effects point to the conclusion that exposure in the third trimester is most likely the driving gestation window ultimately responsible for the newborn's detrimental birth outcomes based on weight, gestational length, and overall health status at birth.

Table 6 presents the IV estimates for the number of days with PM_{10} concentration level above the EU limit over the pregnancy (Panel A) and in each trimester (Panel B).

[Table 6: about here]

The results in Panel A of Table 6 follow a similar pattern as before, pointing to an adverse effect of particulate pollution on the outcomes based on weight, gestation, and physical condition at birth. In particular, ten additional days with PM_{10} concentration level above the EU limit would statistically significantly decrease the newborn's BW by 4.89 grams as well as GEST by about 0.16 days, which corresponds to a reduction of 0.15% and 0.06%, on average, respectively. The associated point estimates are almost 0.002 for LBW, 0.001 for VLBW, 0.003 for PTB, and 0.004 for low Apgar score (APGAR). These estimates imply that ten additional days with PM_{10} value above the threshold would lead to a 4.0% (10%) increase in the prevalence of LBW (VLBW), a 6.0% increase in the prevalence of PTB, and a 1.3% increase in the prevalence of low Apgar score, on average.

Analysis by trimester of gestation in Panel B of Table 6 largely confirms the respective pattern emerged for the average pollution measure shown in Table 5, with the largest adverse effects on health at birth in the third trimester. In particular, exposure to ten additional days with PM_{10} concentration level above the EU limit during the third trimester would significantly decrease BW by about 21.08 grams (0.7%) and increase the prevalence of LBW by 0.013 (26%) as well as of VLBW by 0.002 (20%). Finally, it would decrease GEST by almost 0.653 days (0.2%) and increase PTB by 0.012 (24%) as well as low Apgar index by 0.032 (10.3%). These estimates imply that a 0.653-days reduction in gestation would translate into a reduction of 18.66 grams in weight, which is very close to our estimate of the impact on birth weight of 21.08 grams. Therefore, all the results found in Table 5 are confirmed in Table 6 as well.

Altogether, our IV estimates for the effects of PM_{10} exposure on all birth outcomes have the expected signs and are generally highly statistically significant for both pollution measures adopted in this study, pointing to a robust negative effect of particulate pollution on fetal development while *in utero* across model specifications. If we compare the IV estimates with the OLS estimates, interesting differences emerge both in terms of statistical significance and in magnitude. To begin with, the analysis of the most critical windows of gestation suggests that the fetus is extremely sensitive to air pollution during the third trimester when it increases in weight, which allows us to conclude that the last gestational phase is the most susceptible period of prenatal exposure. This implies that the adverse effect of pollution exposure in the early gestational phase, emerged from the OLS estimates, is spurious. Moreover, the coefficients on PM_{10} in the IV models are almost two to four times larger in absolute values than the OLS ones, depending on the birth outcome and gestation period considered. A closer look at the coefficients reveals a positive correlation between air quality and the error term υ_{itm} in our setup, introducing a downward bias in the OLS estimates of β and β_k in equations (1) and (2). This indicates that the endogeneity issue is non-negligible and its ignorance leads to biased OLS estimates.

Considering the results in Tables 5 and 6, we can argue that maternal exposure to PM_{10} during pregnancy might be an important global risk factor for the newborns' health, especially for the newborns at risk, potentially leading to increased postnatal mortality (Malley et al., 2017; Sun et al., 2016).

Our findings for PM_{10} are broadly in line with the economic literature documenting the detrimental effects of prenatal air pollution on birth outcomes, especially when exposed in the third trimester (Yang et al., 2017). However, as mentioned in Section 2, the economic literature linking maternal exposure to PM_{10} and birth outcomes is scarce, investigating in most cases infant mortality in response to exposure to other air pollutants, mainly SO_2 and

CO. Currie et al. (2009) is one of the few exceptions because they investigate the effects of exposure to CO, O_3, as well as PM_{10}, both during and after birth. However, they find inconsistent effects for PM_{10} across specifications, while the point coefficients for CO exposure are more coherent. In their most complete specification that includes monitor-quarter fixed effects and controls for mother fixed effects, the estimates for prenatal exposure to CO in the third trimester of gestation suggest that a one unit increase in the mean level of CO would reduce birth weight by about 0.5%, increase low birth weight by almost 8%, and shorten gestation by about 0.2%. These estimates are roughly two to six times larger than ours, though they refer to CO effects and not to PM_{10}. In the same spirit, Lavaine and Neidell (2017) find that birth weight and gestational age of the newborns are particularly affected by exposure to SO_2 during the first and the third trimesters of pregnancy, with the estimates in the third trimester being much larger than ours for PM_{10}. Finally, in the study by Currie and Walker (2011) focusing on the reduction of air emissions caused by the introduction of electronic toll collection (E-ZPass), the associated reduced NO_2 levels substantially decreased the incidence of prematurity and low birth weight in the vicinity of toll plazas.

Overall the estimates for CO, SO_2, and NO_2 found in these studies, though reasonable, are larger than those we find for PM_{10}. One exception is found in Chay and Greenstone (2003) who focus on the effects of a decline in TSP (Total Suspended Particles), a pollutant referring to larger particles than PM_{10}, on birth weight and infant mortality. The associated estimates of birth weight are much smaller for PM_{10} than for CO, SO_2, and NO_2 obtained from other studies, which suggests that our PM_{10} effects, although smaller, are plausible.

5.2.2 Threats to Identification

We briefly consider possible threats to validity relevant for a causal interpretation of the estimates in Tables 5 and 6. An initial concern comes from the fact that if rainfall fluctuations, conditional on other covariates, directly affect health at birth, our identifying assumption would be violated. This would be the case, for example, if pregnant women suffer from rainfall variation, with an indirect effect on fetal health leading to worse birth outcomes. To exclude the existence of direct effects, we first analyze the existing evidence from prior studies and then provide some additional evidence supporting the validity of our instrument.

In related studies, researchers generally include, upon data availability, a rich set of controls for weather conditions (e.g., wind speed and direction, humidity, fog, precipitation, and temperature) to account for independent effects of weather shocks on human health (Samet et al., 1998). Nevertheless, they do not systematically discuss the relevance of each meteorological phenomenon in the relation between air pollution and health at birth (Arceo et al., 2016, among others). Moreover, even when the set of weather controls is rich as in Bharadwaj et al. (2017), the statistical significance of these variables is not showed, making it difficult to comment on the direction and magnitude of their potential correlation with birth outcomes. One exception is the study by Currie et al. (2009), who control for daily precipitation as well as daily minimum and maximum temperature. Interestingly, while temperature is a significant predictor of birth outcomes, precipitation variability does not significantly affect health at birth. This finding is in line with the evidence that temperature extremes can have a direct effect on maternal behavior and fetal health (Deschênes et al., 2009; Deschênes and Greenstone, 2011) and suggests that temperature fluctuations, rather than variation in rainfall shocks, can directly influence birth outcomes. At the same time, it underscores the importance to control for temperature for the exclusion restriction to hold in our setting.

To provide further evidence that fluctuations in rainfall do not directly affect birth outcomes we run four tests. First, suppose that hospital personnel or pregnant women have a preference for sunny days and systematically avoid rainy days for deliveries. In case of severe rainy forecast, this preference would lead to a reschedule of deliveries either to an earlier or a later date. This avoidance behavior would ultimately result in sample selection, acting through anticipation or postponement of deliveries, and therefore biased estimates as our instrument would not be anymore as-good-as-random. To test this hypothesis, after collapsing the dataset at municipality and delivery day level, we regress the total number of births on five rainy dummies (one indicating whether the delivery day was rainy or not, two daily lags to capture the anticipation effects as well as two daily leads to capture the postponement effects) controlling for municipality and day-of-week fixed effects. We then divide total births by type of delivery (scheduled c-sections, in labor c-sections as well as spontaneous births) to isolate the effect of rainy days on scheduled c-section births, which might be more subject to rescheduling. Figure 6 shows that rainfall variability does not have a significant impact on the birth outcomes considered. On the vertical axis we plot the associated coefficients, which turn out to be not significant for all temporal dummies of interest across the outcomes considered. We find it particularly reassuring to detect no effect on scheduled c-section births, whose rescheduling just slightly around the due date is a routine hospital practice. Our results show, however, that this kind of surgical intervention is unlikely to be rescheduled in response to some weather preferences.

[Figure 6: about here]

Second, in the spirit of Angrist and Pischke (2009), we look at the reduced form relationship between rainfall variation and health at birth. To this end, we regress the cumulated rain during pregnancy on birth outcomes, separately for municipalities with above and below mean PM_{10}[17]. The idea is to test for possible direct effects of rainfall shocks on fetal development while in the womb. It seems plausible to assume that in the absence of this potential direct effect, babies born in municipalities with better air quality, i.e. a relatively low PM_{10} concentration level, should not be affected by rainfall fluctuations during gestation. On the contrary, weather conditions should have a significant positive impact on health outcomes of babies born in more polluted municipalities, i.e. with relatively high PM_{10} concentration level.

[17] To reduce endogeneity, we separate the municipalities in two groups, one below and one above the mean of PM_{10} calculated for each municipality during 2002, i.e. one year before our period of analysis. Unfortunately, we could not use years before 2002 to compute the pollution mean because the limited number of monitoring stations before 2002 would have excessively reduced the number of municipalities in the sample. Reassuringly, identical results were obtained when considering the PM_{10} mean based on the period 2003-2008 (full sample). Similar results are obtained by dividing municipalities below and above the median PM_{10} concentration level. All results are available upon request.

[Table 7: about here]

Table 7 presents the estimated effects for municipalities with above mean PM_{10} (Panel A) and below mean PM_{10} (Panel B). Significant effects only in the more polluted municipalities support the idea that rainfall positively affects health at birth exclusively through its impact on air pollution mitigation. Third, we regress maternal characteristics such as age, citizenship, education level, labor market status, marital status, and past pregnancy experience on average PM_{10} level and number of days with PM_{10} level above the threshold, during pregnancy respectively. The underlying idea is that air pollution should have no effect on maternal predetermined characteristics and therefore the pollution coefficients should be zero.

[Table 8: about here]

The estimates in Table 8 broadly confirm our hypothesis. In fact, the estimated effects on the aforementioned characteristics are near zero and statistically insignificant. Based on the results from the balancing test, we can conclude that the estimated health effects of prenatal exposure to PM_{10} are not driven by differences in the composition of mothers according to the pollution level in the municipality of residence.

Fourth, we additionally test whether there is evidence of an increased number of hospitalizations in the female population during rainy days. The underlying idea is to identify the direct effect, if any, of rainfall days on pregnant mother's health which in turn might impact on the fetus. In particular, we analyze the effect of rainfall days in the day of hospitalization and up to two days before a hospitalization event on hospitalizations of women related to a particular diagnosis. To this aim, we use the Hospital Discharge Data (HDD, henceforth) provided by the Italian Ministry of Health, which include detailed information on daily hospitalization events occurred both in public and private hospitals for the whole Italian population. We apply the same restrictions as in the birth data, limiting the sample to women aged 15-45. Then, based on the exact primary clinical diagnoses as reported by the ICD-9 codes included in the HDD, we limit our sample to hospitalization episodes related to four main categories of diseases, and precisely pneumonia and influenza, acute pulmonary diseases, mental diseases, and nervous system disorders. Given that we do not have hospitalization data in year 2003, our period of analysis based on HDD data is from 2004 to 2008 for a total of 14,395,843 municipality-day cells. However, this balanced panel covers about 83% of time span of the birth data.

[Table 9: about here]

The results in Table 9 show statistically insignificant coefficients across diagnoses. One small exception is the effect of rain on hospitalizations due to nervous system disorders, though the magnitude is negligible and weakly significant. In line with this evidence, we can not detect a direct effect of rainfall shocks on maternal health deterioration measured by hospitalization episodes potentially related to weather conditions and we can fairly conclude that our instrument is likely to satisfy the exclusion restriction required to consistently estimate the effects of prenatal exposure to PM_{10} on birth outcomes.

6 Effects Heterogeneity and Alternative Specifications

In this section, we explore the treatment effect heterogeneity based on maternal socio-economic status (see Section 6.1), the robustness of our findings to a different sample selection (see Section 6.2) and to multiple hypothesis testing (see Section 6.3).

6.1 Treatment Effect Heterogeneity

Based on our main findings supporting the idea that air pollution is a public bad - as opposed to a public good - , we investigate to what extent its burdens are shared equally across various socio-economic groups in the population, thus contributing to the debate on environmental justice.[18] The idea underlying the concept of environmental inequality is that more disadvantaged groups, for instance low-income groups or ethnic minorities, bear disproportionate environmental burdens, in the form of polluted air and water, unsafe jobs, and under-enforcement of environmental laws (Evans and Kantrowitz, 2002). A number of measures for socio-economic status (SES) has been adopted in the literature, including income, wealth, education, labor force status, and race/ethnicity to show that health effects of air pollution are larger for low SES groups (Neidell, 2004, among others). For instance, low SES groups may be more likely to live in areas with higher average levels of air pollution, next to industrial districts for example, and at the same time less likely to move from one area to another to avoid pollution.

Early-life exposure to air pollution is acknowledged to significantly affect children's health as well as their future educational and labor market outcomes. In this respect, environmental inequality can reinforce its negative impact, especially when exposure starts already in the womb (Currie, 2011). To investigate to what extent air pollution can be considered a socio-economic issue, we analyze the effects of prenatal exposure to PM_{10} on birth outcomes by maternal labor market status as well as by maternal education level. We define low SES mothers as unemployed (vs employed) or low-educated (vs mid- and high-educated) mothers and test whether the negative effects of particulate pollution differ with respect to maternal SES. Tables 10 and 11 present the IV estimates of the effect of average PM_{10} exposure and number of days with PM_{10} exposure above the EU limit, respectively, during pregnancy on birth outcomes by maternal employment status. In Panels A, the estimates are obtained for the subsample of mothers who declared to be employed at delivery, while Panels B report the estimates for the subsample of unemployed mothers at delivery.

[Table 10: about here]

[Table 11: about here]

The results from both tables indicate that babies born to unemployed mothers suffer much

[18] European policy makers have only recently included the notions of environmental justice and environmental equality in their goals (see the recent report by the European Environmental Agency, (EEA, 2018)), which have been part of the US policy objects for almost two decades (Laurent, 2011).

more from particulate pollution in terms of birth outcomes based on weight and, to a lesser extent, on APGAR score.

We observe the same pattern when estimating the effects of PM_{10} exposure during pregnancy with respect to maternal education level in Tables 12 and 13 for both pollution measures. As before, we separate the sample in high-educated mothers (with a high school diploma and above), and low-educated mothers (without a high school diploma). Both tables point to much larger effects of prenatal exposure to pollution in the subsample of mothers with low education. The same results have been found in Yang and Chou (2018), according to which low-educated mothers benefited more from the shutdown of a power plant in Pennsylvania in terms of a greater reduction of PTB and LBW as well as greater increases in average BW and GEST.

[Table 12: about here]

[Table 13: about here]

These pieces of evidence suggest that the health effects at birth differ in size with respect to the maternal socio-economic status. A plausible explanation of these findings could be that unemployed mothers spend more time outdoors being, therefore, more exposed to air pollution, while employed mothers spend large portion of time at work. Furthermore, employed mothers may be more likely to enjoy better air quality in presence of air conditioning that filters air inhaled at work. Finally, high-educated mothers may be better informed about air quality and undertake actions to compensate for the adverse environmental conditions compared to low-educated mothers. Based on this evidence, we can argue that babies born to socially disadvantaged mothers (low SES mothers), are more vulnerable. This implies that the health effect of air pollution are unequally distributed, suggesting that the distribution of environmental quality should be an integral part of environmental policy.

6.2 Extended Sample

We test the robustness of our results to the use of a different sample selection, which extends our unit of observation to municipalities whose centroid falls within a radius of 15 km from the monitors' geographical coordinates as in Currie et al. (2009) and Currie and Neidell (2005). In this respect, if the distance to a monitoring station matters for the accuracy of pollution measures, then we expect weaker results of the effects of prenatal exposure to PM_{10} on birth outcomes in our extended sample.

[Table 14: about here]

[Table 15: about here]

Results from Tables 14 and 15 show that this is indeed the case. For the extended sample, in which environmental data are less precisely merged with birth data, we find smaller and partially wrong-signed estimates that are however not statistically significant. This evidence hints at the importance to use detailed data on mother's location.

6.3 Multiple Hypothesis Tests

Following Romano and Wolf (2005), we test if the standard errors of our main estimates are robust to multiple hypotheses. We estimate alternative p-values to test the significance of a single independent variable when included in a series of regressions with different outcome variables.[19] As independent variables, we separately consider the average PM_{10} and the number of days above the EU concentration limit, both for whole-pregnancy OLS and IV models. The adjusted standard errors obtained from this more demanding inference testing confirm the validity of our main results, with the only exception of APGAR, which is no longer significant in the IV estimates (this set of results is available upon request by the authors).

7 Discussion

Despite the multiple advantages over previous works, our study presents some limitations that deserve to be discussed. Although our data include a wide set of socio-economic controls and we devote effort to address potential endogeneity due to non-random pollution exposure, some issues remain only partially addressed. To begin with, we assume that the temporary mobility of mothers during pregnancy is negligible, but we do not have explicit individual information on this issue. In this respect, richer and more informative longitudinal data would be necessary to fully account for potential avoidance behavior of mothers. Undoubtedly, lack of information on maternal location throughout pregnancy might introduce an exposure misclassification, leading to biased results towards the null. However, current work on potential residential mobility during pregnancy points to low mobility rates and preference for short distances amongst pregnant women (Chen et al., 2010).[20] More recently, using detailed information on all residential addresses between the date of conception and that of delivery, Warren et al. (2017) show that ignorance of residential mobility during pregnancy does not lead to exposure misclassification. Therefore, mobility should not substantially affect our results. A further indication that residential mobility is likely to be of limited concern in our setup derives from the Italian census data, which points to generally high percentages of owned dwellings, ranging from 61.9% in the region of Campania to 78.8% in the region of Molise, registered in 2001 (ISTAT, 2001). Hence, we expect relatively low mobility among resident families. Taken together, underestimation of the true effects of pollution on health at birth due to residential misclassification does not seem highly relevant in our case.

Second, we include in our sample also mothers with region of hospital different from region of residence, which might introduce an attenuation bias due to a potential measurement error in the pollution assignment. From the initial total births population of ca. 3,400,000 mothers,

[19]The test is carried out using the RWOLF Stata command by Clarke (2018).

[20]Potential residential mobility during pregnancy is defined as any change of address between the estimated date of conception and pregnancy termination. A few studies report the frequency, distance, and timing of moves during pregnancy (Bell and Belanger, 2012, among others). The mobility rates range from 9% to 32%, with the highest mobility during the second trimester. Most moves occur once and within short distances, with a median distance of less than 10 km.

only 162,244 of them report region of residence different from that of their hospital of delivery (less than 5%). We cannot reduce the mismatch at the provincial or municipal level because mothers might choose to deliver in a hospital located in a different province in the same region of residence or might be forced to move to the closest municipality with a hospital if their municipality of residence lacks one. In fact, out of almost 8,100 municipalities in Italy, less than 800 have a hospital with a maternity ward. To check to what extent our estimates are sensitive to the inclusion of mothers declaring region of residence different from region of hospital in our sample, we run the estimates by excluding the associated observations. As expected, it turns out that this variation in the sample composition yields slightly larger estimates.[21]

Finally, our analysis is based on population data belonging to a period in which the levels of particulate concentrations were slightly higher than nowadays. Nevertheless, the health response to lower PM_{10} levels experienced today might be of similar order of magnitude if our estimates reflect lower bounds of the true effects. This is likely to be the case since we do not control for selective mortality, implying that the population of surviving newborns is positively selected.

8 Conclusion

This paper investigates the effect of air pollution on birth outcomes. It exploits rainfall shocks as an exogenous source of PM_{10} variation to identify the causal effect of pollution on birth outcomes. We find a clear and robust pattern of an adverse impact of PM_{10} concentrations on weight, gestation duration, and overall physical condition for the newborn population in the early 2000s in Italy. Prenatal exposure during the third trimester of gestation, when the fetus gains weight, reveals to be the most harmful to fetal growth in the womb. Both measures of pollution adopted in this study, average PM_{10} concentrations and number of days with PM_{10} level above the threshold, yield similar results. Moreover, the specific nature of the IV employed allows us to capture the sole effect of PM_{10}, which constitutes a major advantage in studies that employ a single-pollutant model where the potential correlation between air pollutants is neglected. Indeed, rain is tested to be a relevant instrument only for particle pollution, while the correlation with other pollutants such as SO_2, NO_2 and CO is far from being statistically significant.[22] Our paper also contributes to the debate on environmental justice. In this respect, from our analysis of the treatment effect heterogeneity emerges that babies born to socially disadvantaged mothers are more vulnerable, implying that the health effects of air pollution are unequally distributed.

To better understand the importance of our findings, these should be viewed in a broader framework of studies that underscore the relevance of adverse health at birth, especially low birth weight, for outcomes later in life (Black et al., 2007, among others). While they uncover the negative effects of poor health at birth on future child and adult health, education, and

[21]The results from this robustness check are available upon request.

[22]The differential response of air pollutants to different weather conditions is showed also in Knittel et al. (2016).

labor market performance, we shed light on an important risk factor for fetal health, which is *in utero* exposure to PM_{10}. Taken together, our results and those deriving from the related literature suggest that gains from fetal interventions, e.g. through actions directed to reduce air pollution or limit fetuses' exposure, would not dissipate in the long-run. This knowledge gain is of direct policy relevance. In fact, if disadvantaged families are more likely to live in more polluted areas, exposure to air pollution may contribute to explaining the existing differences in educational attainment and labor market outcomes across different socio-economic groups, or more generally, explaining social and economic inequality (Isen et al., 2017). This in turn implies that better air quality may help improve environmental conditions in low-income families and thus align endowments at birth, giving a fair chance in life to every child (Germani et al., 2014). If economic and environmental inequality reinforce each other, then actions directed to improve air quality may serve not only as environmental health policies but also as effective social policies to abate economic inequality. Furthermore, if air pollution is viewed as a factor of production which, similar to technology, is able to impact how other production factors such as labor, capital, and land can be combined to generate output, we argue that improved air quality may also contribute to economic progress. We conclude that more effective air quality regulation aiming to promote environmental justice remains a priority for both Italy and countries with comparable levels or distribution of particulate pollution, as this investment would result in better health outcomes and associated social as well as economic benefits for future generations.

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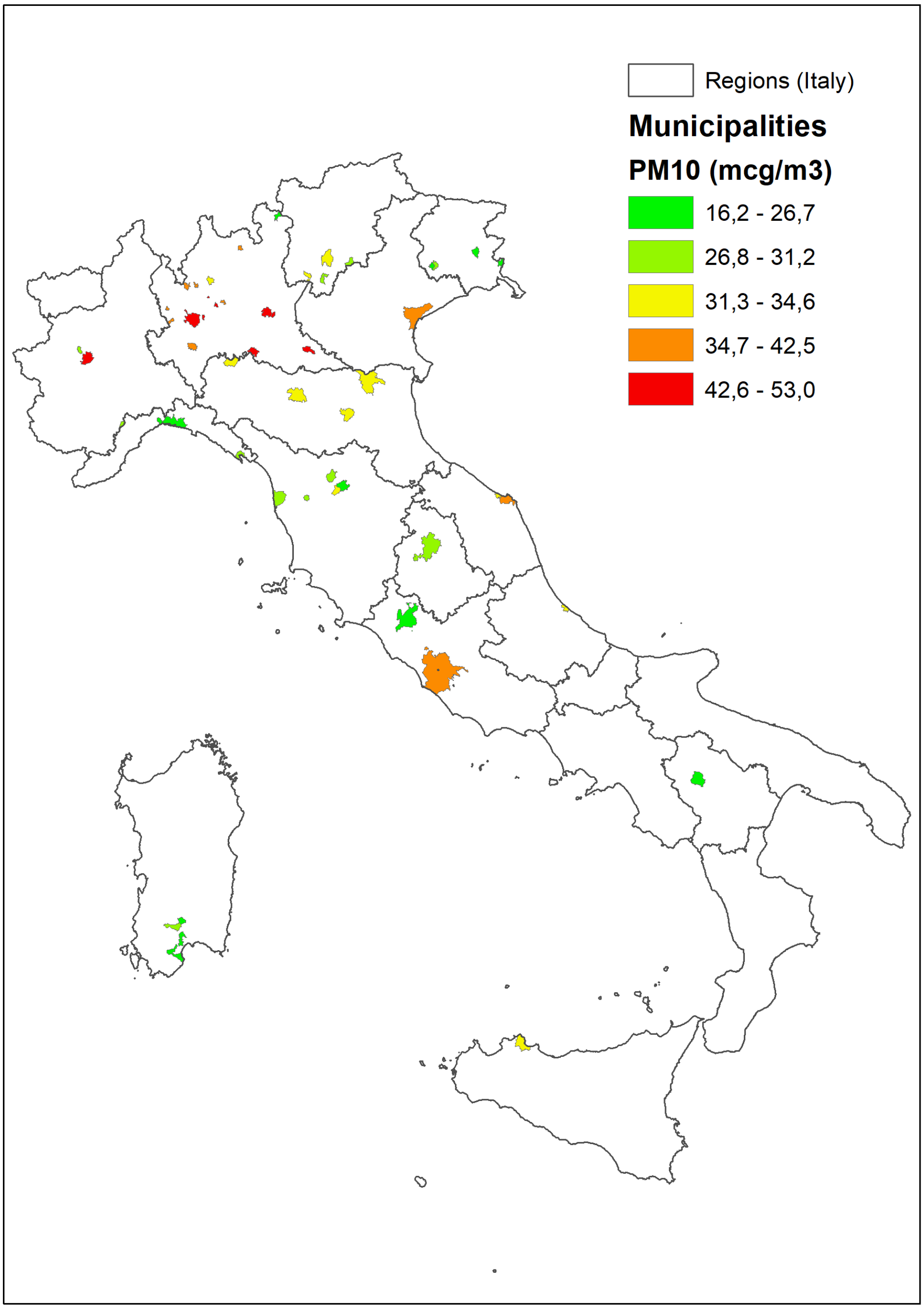
Figures

Figure 1: Location of Municipalities with Monitoring Stations and Annual Average PM_{10} Concentration

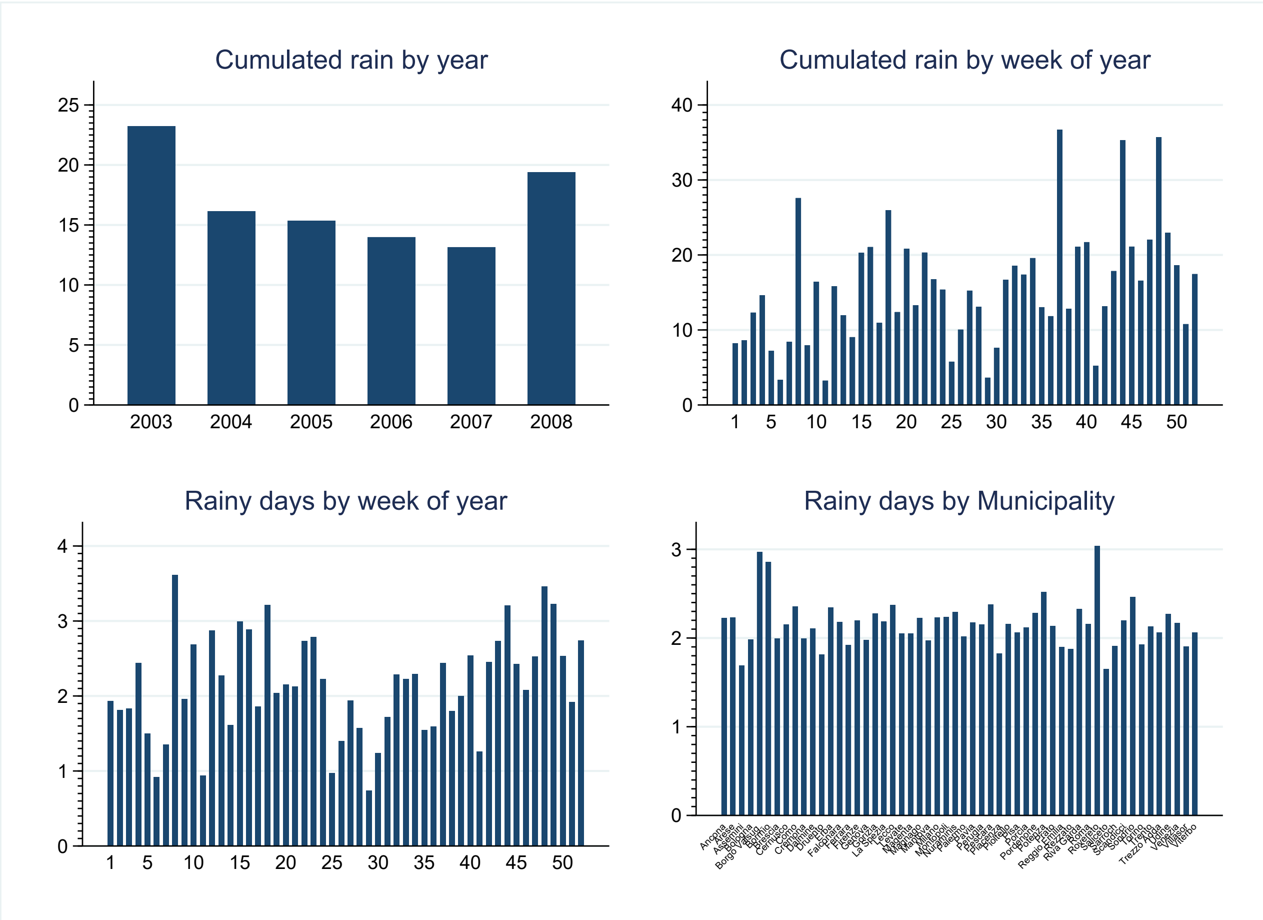


Notes : Data are from the European Air Quality Database (Airbase), maintained by the European Environmental Agency through the European topic center on Air Pollution and Climate Change mitigation.

Figure 2: Weekly Average PM_{10} Levels in Each in-sample Municipality during the Period 2003-2008

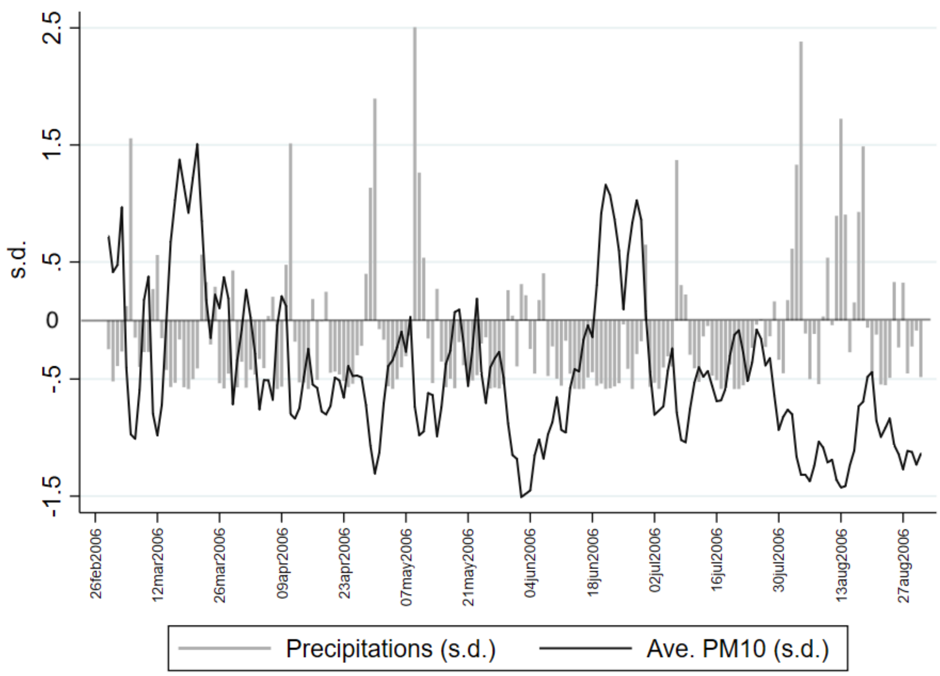
Notes : The graphs plot weekly residual air pollution levels in each municipality adjusting for time and municipality fixed effects, windspeed and average temperature.

Figure 3: Rain Distribution



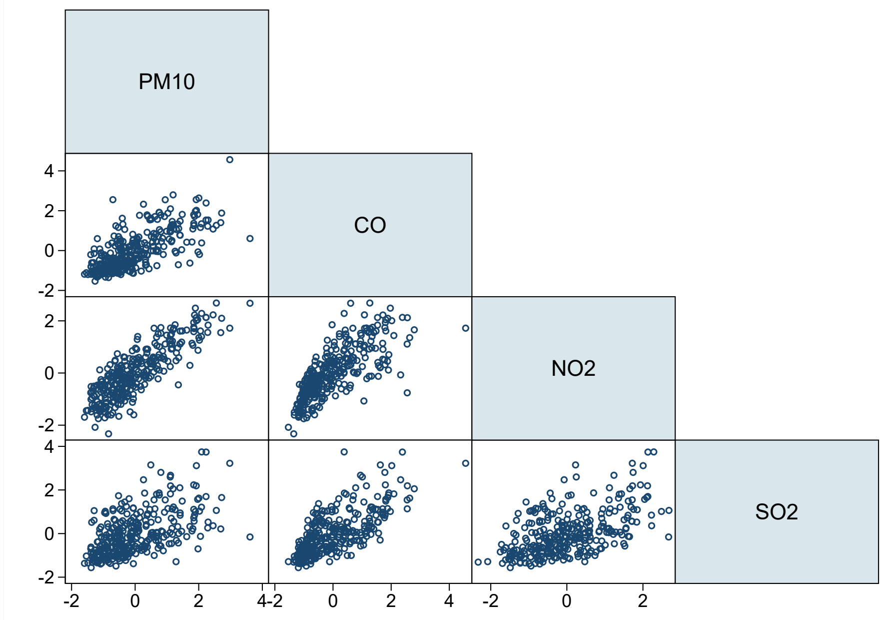
Notes : The figure shows the rain distribution across years (top-left panel) and weeks (top-right panel). The bottom-left and bottom-right panels show, respectively, the number of rainy days across weeks and municipalities. Data are from the Gridded Agro-Meteorological Data (CGMS), which contain daily meteorological parameters from weather stations interpolated on a 25x25 km grid over the whole Italian territory.

Figure 4: Daily Precipitations and Average PM_{10} in 2006



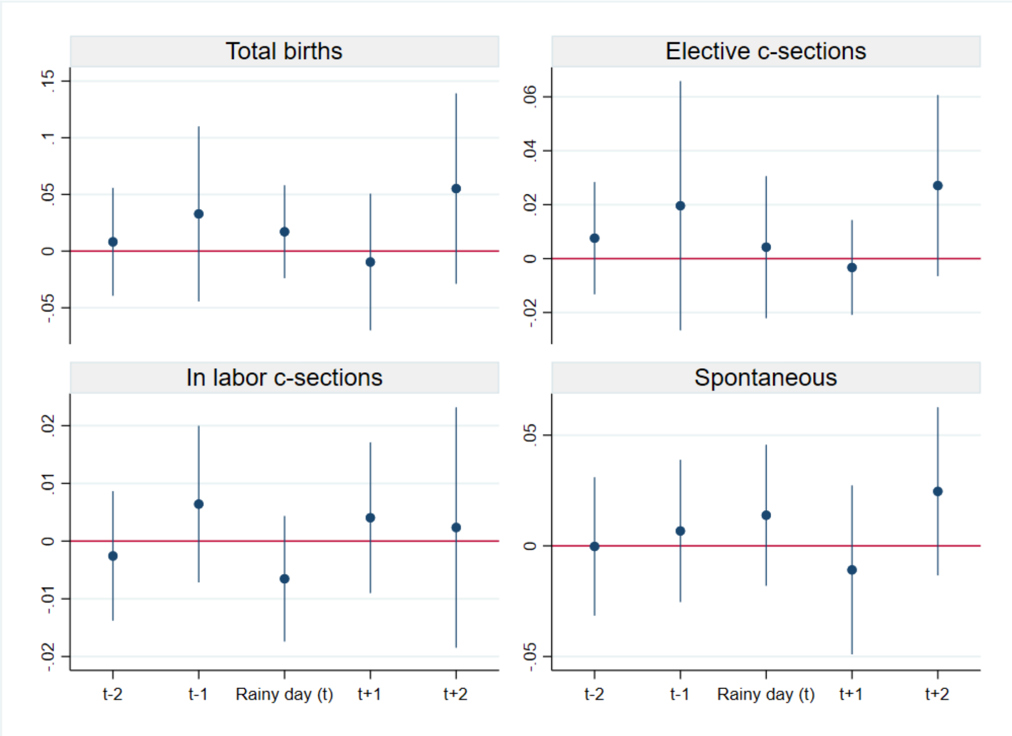
Notes : The figure plots precipitation and PM_{10} daily fluctuations, both demeaned and standardized, during 2006 (patterns for other years are similar). The figure is obtained by combining monitoring station data from the AirBase database and the Gridded Agro-Meteorological Data.

Figure 5: Correlation between Pollutants



Notes : The figure shows weekly correlations across PM_{10}, CO, NO_2 and SO_2 using monitoring station data from the AirBase database.

Figure 6: The Effect of Timing of Rainy Days on Number of Births by Type of Delivery



Notes : The figure plots point estimates of the effect of rain on the number of different types of deliveries. The estimates are obtained by collapsing the dataset at municipality and delivery day level and regressing the number of births on five rainy dummies (one indicating whether the delivery day was rainy or not, two daily lags and two daily leads) controlling for municipality and day of week fixed effects. The top-left panel shows the effects on total births, the right-top panel the effects on elective c-section deliveries, the left-bottom panel the effects on in labor c-section deliveries, while the right-bottom panel the effects on spontaneous deliveries.

Tables

Table 1: Summary Statistics

	Mean	SD
Panel A: Outcomes		
Birth Weight (grams) (BW)	3,272.12	247.97
Low Birth Weight (LBW)	0.05	0.11
Very Low Birth Weight (VLBW)	0.01	0.04
Intra-Uterine Growth Restriction (IUGR)	0.02	0.08
Gestation (days) (GEST)	273.27	6.09
Pre-Term Birth (PTB)	0.05	0.11
Low Apgar score (APGAR)	0.31	1.73
Panel B: Pollution Measures		
Mean PM_{10} exposure during pregnancy (mcg/m3)	34.73	10.22
# Days with PM_{10} above the EU limit during pregnancy	54.77	37.13
Panel C: Control Variables		
Age of mother	32.28	2.54
Female child	0.49	0.25
Foreign mother	0.19	0.21
Education: less than high school	0.30	0.25
Education: high school	0.44	0.25
Education: more than high school	0.26	0.22
Housewife	0.34	0.25
Dependent employee	0.56	0.26
Self-employed	0.10	0.15
Employed mother	0.68	0.24
Married mother	0.73	0.25
Previous births	0.45	0.25
Previous abortions	0.20	0.20
Type of hospital: public	0.91	0.19
Type of hospital: private	0.07	0.17
Type of hospital: missing	0.01	0.08
Pediatrician: absent	0.31	0.31
Pediatrician: present	0.58	0.34
Pediatrician: missing	0.11	0.28
Municipal income (ave. gross per capita)	23,731.49	3,156.90
Panel D: Environmental Variables		
Mean of daily minimum temperature during pregnancy	9.18	3.40
Mean of daily maximum temperature during pregnancy	18.80	3.67
Cumulated rain during pregnancy (mm)	598.61	224.63

Notes:N=12,260.

Table 2: OLS Estimates of the Effect of Average PM_{10} Exposure during Pregnancy and in each Trimester on Birth Outcomes

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
Mean	[3,272.12]	[0.05]	[0.01]	[0.02]	[273.27]	[0.05]	[0.31]
(sd)	(247.97)	(0.11)	(0.04)	(0.08)	(6.09)	(0.11)	(1.73)
Panel A							
Average PM_{10} (mcg/m3)	-10.346***	0.003***	0.000	0.001	-0.187**	0.004**	0.006**
	(1.917)	(0.001)	(0.000)	(0.001)	(0.070)	(0.002)	(0.003)
Panel B							
Avg PM_{10} (mcg/m3), trimester I	-5.199***	0.002*	-0.000	0.000	-0.120**	0.002**	0.003
	(1.406)	(0.001)	(0.000)	(0.001)	(0.054)	(0.001)	(0.002)
Avg PM_{10} (mcg/m3), trimester II	1.431	-0.001	-0.001	0.000	0.079	-0.001	-0.005
	(2.419)	(0.001)	(0.000)	(0.000)	(0.066)	(0.001)	(0.003)
Avg PM_{10} (mcg/m3), trimester III	-8.037***	0.003**	0.001	0.001*	-0.183***	0.004***	0.009**
	(2.170)	(0.001)	(0.000)	(0.000)	(0.059)	(0.001)	(0.004)

Notes: Panel A reports the IV estimates of the effect of no. of days with PM_{10} exposure above the EU limit during pregnancy on birth outcomes using the cumulated rain over pregnancy as an instrument; Panel B reports the IV estimates of the effect of no. of days with PM_{10} exposure above the EU limit in each trimester of pregnancy on birth outcomes using the cumulated rain in each trimester as an instrument. Pollution coefficients show the effect of an increase by 10 in days with PM_{10} above EU limit. The unit of observation is the municipality-week-of-birth cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy (Panel A) or in each trimester (Panel B). Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 12,260 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: OLS Estimates of the Effect of no. of Days with PM_{10} Exposure above the EU limit during Pregnancy and in each Trimester on Birth Outcomes

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
Mean	[3,272.12]	[0.05]	[0.01]	[0.02]	[273.27]	[0.05]	[0.31]
(sd)	(247.97)	(0.11)	(0.04)	(0.08)	(6.09)	(0.11)	(1.73)
Panel A							
# Days with PM_{10} above EU limit	-2.584***	0.001***	0.000	0.000*	-0.033	0.001***	0.001
	(0.501)	(0.000)	(0.000)	(0.000)	(0.024)	(0.000)	(0.001)
Panel B							
# Days with PM_{10} above EU limit, trim. I	-4.479***	0.002**	0.000	0.001**	-0.086*	0.002***	0.003*
	(1.031)	(0.001)	(0.000)	(0.000)	(0.051)	(0.001)	(0.002)
# Days with PM_{10} above EU limit, trim. II	1.214	-0.001	-0.001**	-0.000	0.081*	-0.001**	-0.004*
	(1.541)	(0.001)	(0.000)	(0.000)	(0.044)	(0.001)	(0.002)
# Days with PM_{10} above EU limit, trim. III	-5.676***	0.003***	0.001**	0.001**	-0.122***	0.003***	0.006***
	(1.351)	(0.001)	(0.000)	(0.000)	(0.044)	(0.001)	(0.002)

Notes: Panel A reports the OLS estimates of the effect of no. of days with PM_{10} exposure above the EU limit during pregnancy on birth outcomes; Panel B reports the OLS estimates of no. of days with PM_{10} exposure above the EU limit in each trimester of pregnancy on birth outcomes. Pollution coefficients show the effect of an increase by ten in days with PM_{10} above EU limit. The unit of observation is the municipality-week-of-birth cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy (Panel A) or in each trimester (Panel B). Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 12,260 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: First Stage Estimates of the Effect of Cumulated Rain on PM_{10}

Panel A - Avg PM_{10} (mcg/m3)			
Cumulated rain (mm) during pregnancy		-0.156**	
		(0.049)	
F-stat		9.82	
	Trimester I	Trimester II	Trimester III
Cumulated rain (mm) during trim. I	-0.288***	-0.108**	0.015
	(0.074)	(0.049)	(0.036)
Cumulated rain (mm) during trim. II	-0.068	-0.323***	-0.139**
	(0.057)	(0.076)	(0.046)
Cumulated rain (mm) during trim. III	0.026	-0.078	-0.263***
	(0.059)	(0.057)	(0.071)
F-stat	26.99	38.15	16.27
Panel B - # Days with PM_{10} above EU limit			
Cumulated rain (mm) during pregnancy		-0.551***	
		(0.162)	
F-stat		11.6	
	Trimester I	Trimester II	Trimester III
Cumulated rain (mm) during trim. I	-0.370***	-0.092	-0.013
	(0.098)	(0.067)	(0.005)
Cumulated rain (mm) during trim. II	-0.073	-0.377***	-0.128**
	(0.077)	(0.085)	(0.054)
Cumulated rain (mm) during trim. III	0.008	0.081	-0.303***
	(0.080)	(0.071)	(0.085)
F-stat	26.90	26.10	14.45

Notes: Panel A reports the first stage estimates of the effect of cumulated rain on average PM_{10} during pregnancy and in each trimester; Panel B reports the first stage estimates of the effect of cumulated rain on no. of days with PM_{10} exposure above the EU limit during pregnancy and in each trimester. The coefficients show the effect of an increase by 10 mm in the cumulated rain. The unit of observation is the municipality-week-of-birth cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy or in each trimester. Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 12,260 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: IV Estimates of the Effect of Average PM_{10} Exposure during Pregnancy and in each Trimester on Birth Outcomes

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
Mean	[3,272.12]	[0.05]	[0.01]	[0.02]	[273.27]	[0.05]	[0.31]
(sd)	(247.97)	(0.11)	(0.04)	(0.08)	(6.09)	(0.11)	(1.73)
Panel A							
Average PM_{10} (mcg/m3)	-17.210***	0.009***	0.002**	0.003	-0.559**	0.010***	0.015
	(5.089)	(0.003)	(0.001)	(0.002)	(0.224)	(0.004)	(0.009)
Panel B							
Avg PM_{10} (mcg/m3), trimester I	-8.799	0.004	0.000	0.002	-0.250*	0.001	-0.007
	(6.406)	(0.003)	(0.001)	(0.002)	(0.146)	(0.003)	(0.016)
Avg PM_{10} (mcg/m3), trimester II	11.949	-0.009**	-0.001	-0.001	0.292	-0.003	-0.014
	(10.706)	(0.005)	(0.002)	(0.001)	(0.298)	(0.006)	(0.017)
Avg PM_{10} (mcg/m3), trimester III	-26.601***	0.017***	0.003**	0.003	-0.818***	0.014**	0.038**
	(8.212)	(0.004)	(0.001)	(0.002)	(0.210)	(0.006)	(0.015)

Notes: Panel A reports the IV estimates of the effect of average PM_{10} exposure during pregnancy on birth outcomes using the cumulated rain over pregnancy as an instrument; Panel B reports the IV estimates of the effect of average PM_{10} exposure in each trimester of pregnancy on birth outcomes using the cumulated rain in each trimester as an instrument. Pollution coefficients show the effect of an increase by 10 in the average PM_{10}. The unit of observation is the municipality-week-of-birth cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy (Panel A) or in each trimester (Panel B). Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 12,260 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: IV Estimates of the Effect of no. of Days with PM_{10} Exposure above the EU Limit during Pregnancy and in each Trimester on Birth Outcomes

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
Mean	[3,272.12]	[0.05]	[0.01]	[0.02]	[273.27]	[0.05]	[0.31]
(sd)	(247.97)	(0.11)	(0.04)	(0.08)	(6.09)	(0.11)	(1.73)
Panel A							
# Days with PM_{10} above EU limit	-4.885***	0.002***	0.001**	0.001	-0.159**	0.003***	0.004*
	(1.370)	(0.001)	(0.000)	(0.001)	(0.060)	(0.001)	(0.002)
Panel B							
# Days with PM_{10} above EU limit, trim. I	-3.142	0.001	-0.000	0.001	-0.087	-0.001	-0.010
	(3.239)	(0.002)	(0.001)	(0.001)	(0.115)	(0.001)	(0.010)
# Days with PM_{10} above EU limit, trim. II	6.595	-0.006	-0.001	-0.000	0.142	-0.001	-0.008
	(8.200)	(0.004)	(0.001)	(0.001)	(0.234)	(0.005)	(0.013)
# Days with PM_{10} above EU limit, trim. III	-21.084***	0.013***	0.002**	0.002	-0.653***	0.012**	0.032***
	(6.857)	(0.003)	(0.001)	(0.002)	(0.169)	(0.005)	(0.011)

Notes: Panel A reports the OLS estimates of the effect of average PM_{10} exposure during pregnancy on birth outcomes; Panel B reports the OLS estimates of the effect of average PM_{10} exposure in each trimester of pregnancy on birth outcomes. Pollution coefficients show the effect of an increase by ten in the average PM_{10}. The unit of observation is the municipality-week-of-birth cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All regressions control for maternal and child characteristics: age, age squared, marital status (married=1), education level (less than high school (reference), high school, more than high school), labor market attachment (employed=1), professional position (housewife (reference), self-employed, dependent employee), child's sex (female=1), neonatal pediatrician at delivery (present (reference), absent, missing), type of hospital (public (reference), private, missing), citizenship (foreign=1), previous abortions including voluntary interruptions of pregnancy as well as miscarriages (yes=1), previous deliveries (yes=1). Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy (Panel A) or in each trimester (Panel B). Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 12,260 observations. * $p <0.1$, ** $p <0.05$, *** $p <0.01$.

Table 7: The Effect of Rainfall during Pregnancy on Birth Outcomes by Level of PM_{10}

	BW	LBW	VLBW	IUGR	GEST	PTB	APGAR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Municipalities with above mean PM_{10}						
Cumulated rain during pregnancy (mm)	0.0387***	-0.0001*	-0.0001***	-0.0001**	0.0005*	-0.0001*	-0.0003
	(0.010)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Panel B: Municipalities with below mean PM_{10}						
Cumulated rain during pregnancy (mm)	0.0253	-0.0000	0.0000	0.0000	0.0006	-0.0000	0.0003
	(0.016)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: Panel A reports the estimates of the effect of cumulated rain during pregnancy on birth outcomes in municipalities with above mean PM_{10} level; Panel B reports the estimates of the effect of cumulated rain during pregnancy on birth outcomes in municipalities with below mean PM_{10} level. The unit of observation is the municipality-week-of-year cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-year fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy. Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 4,361 observations for Panel A and 2,844 observations for Panel B. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: OLS Estimates of the Effect of Maternal Characteristics on PM_{10} Exposure

VARIABLES	Average PM_{10} (mcg/m3)	# Days with PM_{10} above EU limit
	(1)	(2)
Age of mother	0.000	-0.000
	(0.000)	(0.001)
Foreign	-0.003	0.027
	(0.009)	(0.022)
High education	0.008	0.031
	(0.011)	(0.035)
Employed	0.001	0.003
	(0.004)	(0.014)
Married	0.006	0.029
	(0.004)	(0.020)
Pregnancy experience	0.003	0.018
	(0.007)	(0.016)

Notes: Column (1) reports the OLS estimates of the effect of maternal characteristics on the average PM_{10} concentration level during pregnancy; Column (2) reports the OLS estimates of the effect of maternal characteristics on the no. of days with PM_{10} concentration level above the EU limit during pregnancy. The unit of observation is delivery, based on individual data. Each coefficient is from a separate regression, which includes municipality fixed effects and day-of-year fixed effects. Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 432,640 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: OLS Estimates of the Effect of Weather Conditions on the Number of Hospitalizations by Diagnosis

	Pneumonia Influenza (1)	Acute Pulmonary Disease (2)	Mental Disease (3)	Nervous System Disorder (4)
Rain in t	-0.000003	-0.000002	0.000019	0.000053*
	(0.000003)	(0.000002)	(0.000020)	(0.000029)
Rain in (t-1)	0.000001	0.000002	0.000015	0.000046
	(0.000003)	(0.000002)	(0.000020)	(0.000029)
Rain in (t-2)	0.000003	0.000001	0.000006	0.000044
	(0.000003)	(0.000002)	(0.000019)	(0.000029)
Max Temp	-0.000000	-0.000000	0.000004	0.000003
	(0.000000)	(0.000000)	(0.000004)	(0.000005)
Max Temp (t-1)	0.000000	0.000000	0.000000	0.000004
	(0.000001)	(0.000000)	(0.000004)	(0.000006)
Max Temp (t-2)	-0.000000	-0.000000	0.000003	0.000003
	(0.000000)	(0.000000)	(0.000004)	(0.000005)
Min Temp	-0.000000	-0.000000	-0.000005	-0.000012*
	(0.000001)	(0.000000)	(0.000005)	(0.000007)
Min Temp (t-1)	-0.000000	0.000000	0.000002	0.000004
	(0.000001)	(0.000000)	(0.000005)	(0.000007)
Min Temp (t-2)	-0.000000	0.000000	-0.000003	0.000002
	(0.000001)	(0.000000)	(0.000004)	(0.000006)

Notes: The Table reports the OLS estimates of the effects of rain and temperature in the day of hospitalization and up to 2 days before hospitalization on the number of hospitalizations per 1,000 residents. The estimates are obtained from 4 separate regressions, one per diagnosis, and include municipality fixed effects and day fixed effects. The unit of observation is the municipality-day cell. The estimates are weighted by the number of women in each municipality-year. Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 14,395,843 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: IV Estimates of the Effect of Average PM_{10} Exposure during Pregnancy on Birth Outcomes by Mother's Employment Status

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
				Panel A: Employed Mothers			
Mean	[3,272.61]	[0.04]	[0.006]	[0.02]	[273.31]	[0.05]	[0.02]
(sd)	(266.87)	(0.11)	(0.04)	(0.087)	(6.53)	(0.11)	(0.16)
Average PM_{10} (mcg/m3)	-7.920*	0.006**	0.001	0.004	-0.479**	0.008**	-0.001
	(4.534)	(0.003)	(0.001)	(0.003)	(0.193)	(0.003)	(0.005)
				Panel B: Unemployed Mothers			
Mean	[3,280.48]	[0.05]	[0.01]	[0.02]	[273.17]	[0.06]	[0.04]
(sd)	(319.19)	(0.14)	(0.05)	(0.10)	(7.65)	(0.14)	(0.20)
Average PM_{10} (mcg/m3)	-30.048**	0.008*	0.003	0.000	-0.633*	0.011	0.026*
	(13.761)	(0.004)	(0.002)	(0.003)	(0.352)	(0.007)	(0.015)

Notes: Panel A reports the IV estimates of the effect of average PM_{10} exposure during pregnancy on birth outcomes for employed mothers using the cumulated rain over pregnancy as an instrument; Panel B reports the IV estimates of the effect of average PM_{10} exposure during pregnancy on birth outcomes for unemployed mothers using the cumulated rain over pregnancy as an instrument. Pollution coefficients show the effect of an increase by ten in the average PM_{10}. The unit of observation is the municipality-week-of-birth cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy. Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 11,676 observations for employed mothers and 10,100 observations for unemployed mothers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: IV Estimates of the Effect of no. of Days with PM_{10} Exposure above the EU Limit during Pregnancy on Birth Outcomes by Mother's Employment Status

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
				Panel A: Employed Mothers			
Mean	[3,272.61]	[0.04]	[0.006]	[0.02]	[273.31]	[0.05]	[0.02]
(sd)	(266.87)	(0.11)	(0.04)	(0.087)	(6.53)	(0.11)	(0.16)
# Days with PM_{10} above EU limit	-2.278*	0.002**	0.000	0.001	-0.138**	0.002***	-0.000
	(1.290)	(0.001)	(0.000)	(0.001)	(0.055)	(0.001)	(0.002)
				Panel B: Unemployed Mothers			
Mean	[3,280.48]	[0.05]	[0.01]	[0.02]	[273.17]	[0.06]	[0.04]
(sd)	(319.19)	(0.14)	(0.05)	(0.10)	(7.65)	(0.14)	(0.20)
# Days with PM_{10} above EU limit	-8.325**	0.002*	0.001	0.000	-0.175*	0.003*	0.007*
	(3.632)	(0.001)	(0.000)	(0.001)	(0.093)	(0.002)	(0.004)

Notes: Panel A reports the IV estimates of the effect of no. of days with PM_{10} exposure above the EU limit during pregnancy on birth outcomes for employed mothers using the cumulated rain over pregnancy as an instrument; Panel B reports the IV estimates of the effect of no. of days with PM_{10} exposure above the EU limit during pregnancy on birth outcomes for unemployed mothers using the cumulated rain over pregnancy as an instrument. Pollution coefficients show the effect of an increase by ten in days with PM_{10} above the EU limit. The unit of observation is the municipality-week-of-birth cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy. Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 11,676 observations for employed mothers and 10,100 observations for unemployed mothers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: IV Estimates of the Effect of Average PM_{10} Exposure during Pregnancy on Birth Outcomes by Mother's Education Level

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
	Panel A: High Educated Mothers						
Mean	[3,282.53]	[0.05]	[0.01]	[0.02]	[273.49]	[0.05]	[0.03]
(sd)	(259.55)	(0.11)	(0.04)	(0.08)	(6.30)	(0.11)	(0.17)
Average PM_{10} (mcg/m3)	-7.433	0.005*	0.001	0.004*	-0.351*	0.009***	0.010
	(5.240)	(0.003)	(0.001)	(0.002)	(0.177)	(0.003)	(0.010)
	Panel B: Low Educated Mothers						
Mean	[3,257.95]	[0.06]	[0.01]	[0.02]	[272.78]	[0.06]	[0.05]
(sd)	(333.25)	(0.15)	(0.05)	(0.10)	(8.04)	(0.16)	(0.21)
Average PM_{10} (mcg/m3)	-30.173***	0.012**	0.004*	0.001	-0.589*	0.010	0.007
	(9.785)	(0.005)	(0.002)	(0.003)	(0.336)	(0.006)	(0.010)

Notes: Panel A reports the IV estimates of the effect of average PM_{10} exposure during pregnancy on birth outcomes for high-educated mothers using the cumulated rain over pregnancy as an instrument; Panel B reports the IV estimates of the effect of average PM_{10} exposure during pregnancy on birth outcomes for low-educated mothers using the cumulated rain over pregnancy as an instrument. Pollution coefficients show the effect of an increase by ten in the average PM_{10}. The unit of observation is the municipality-week-of-birth cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy. Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 11,601 observations for high-educated mothers and 9,963 observations for low-educated mothers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: IV Estimates of the Effect of no. of Days with PM_{10} Exposure above the EU Limit during Pregnancy on Birth Outcomes by Mother's Education Level

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
	Panel A: High Educated Mothers						
Mean	[3,282.53]	[0.05]	[0.01]	[0.02]	[273.49]	[0.05]	[0.03]
(sd)	(259.55)	(0.11)	(0.04)	(0.08)	(6.30)	(0.11)	(0.17)
# Days with PM_{10} above EU limit	-2.112	0.001*	0.000	0.001*	-0.100**	0.002***	0.003
	(1.479)	(0.001)	(0.000)	(0.001)	(0.049)	(0.001)	(0.003)
	Panel B: Low Educated Mothers						
Mean	[3,257.95]	[0.06]	[0.01]	[0.02]	[272.78]	[0.06]	[0.05]
(sd)	(333.25)	(0.15)	(0.05)	(0.10)	(8.04)	(0.16)	(0.21)
# Days with PM_{10} above EU limit	-8.553***	0.003**	0.001*	0.000	-0.167*	0.003*	0.002
	(2.592)	(0.001)	(0.001)	(0.001)	(0.091)	(0.002)	(0.003)

Notes: Panel A reports the IV estimates of the effect of no. of days with PM_{10} exposure above the EU limit during pregnancy on birth outcomes for high-educated mothers using the cumulated rain over pregnancy as an instrument; Panel B reports the IV estimates of the effect of no. of days with PM_{10} exposure above the EU limit during pregnancy on birth outcomes for low-educated mothers using the cumulated rain over pregnancy as an instrument. Pollution coefficients show the effect of an increase by ten in days with PM_{10} above the EU limit. The unit of observation is the municipality-week-of-birth cell. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy. Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 11,601 observations for high-educated mothers and 9,963 observations for low-educated mothers. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 14: IV Estimates of the Effect of Average PM_{10} Exposure during Pregnancy and in each Trimester on Birth Outcomes - Extended Sample

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
Mean	[3,273.37]	[0.05]	[0.01]	[0.02]	[273.28]	[0.05]	[0.01]
(sd)	(403.92)	(0.18)	(0.07)	(0.12)	(9.73)	(0.18)	(0.12)
Panel A							
Average PM_{10} (mcg/m3)	-11.818	0.011	0.004	0.010	1.784	-0.001	0.009
	(34.623)	(0.016)	(0.007)	(0.014)	(1.911)	(0.011)	(0.029)
Panel B							
Avg PM_{10} (mcg/m3), trimester I	-13.442	0.006	0.000	0.007	1.084	-0.003	-0.012
	(27.134)	(0.013)	(0.005)	(0.011)	(1.456)	(0.009)	(0.014)
Avg PM_{10} (mcg/m3), trimester II	-1.531	-0.001	0.004	-0.003	0.521	-0.006	0.019
	(16.251)	(0.010)	(0.003)	(0.008)	(0.739)	(0.010)	(0.023)
Avg PM_{10} (mcg/m3), trimester III	2.180	0.011	-0.002	0.014	0.959	0.009	0.000
	(26.828)	(0.013)	(0.004)	(0.013)	(1.441)	(0.009)	(0.023)

Notes: Panel A reports the IV estimates of the effect of average PM_{10} exposure during pregnancy on birth outcomes using the cumulated rain over pregnancy as an instrument; Panel B reports the IV estimates of the effect of average PM_{10} exposure in each trimester of pregnancy on birth outcomes using the cumulated rain in each trimester as an instrument. Pollution coefficients show the effect of an increase by 10 in the average PM_{10}. The unit of observation is the municipality-week-of-birth cell, where the definition of municipality is extended to inclusion of municipalities whose centroid falls within a radius of 15 km from the monitor's geographical coordinates. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy (Panel A) or in each trimester (Panel B). Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 13,143 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: IV Estimates of the Effect of no. of Days with PM_{10} Exposure during Pregnancy and in each Trimester on Birth Outcomes - Extended Sample

	BW (1)	LBW (2)	VLBW (3)	IUGR (4)	GEST (5)	PTB (6)	APGAR (7)
Mean	[3,273.37]	[0.05]	[0.01]	[0.02]	[273.28]	[0.05]	[0.01]
(sd)	(403.92)	(0.18)	(0.07)	(0.12)	(9.73)	(0.18)	(0.12)
Panel A							
# Days with PM_{10} above EU limit	-2.727	0.002	0.001	0.002	0.412	-0.000	0.002
	(7.369)	(0.003)	(0.001)	(0.003)	(0.352)	(0.003)	(0.007)
Panel B							
# Days with PM_{10} above EU limit, trim. I	-8.627	0.003	0.001	0.003	0.625	-0.003	-0.007
	(14.811)	(0.007)	(0.003)	(0.006)	(0.667)	(0.005)	(0.008)
# Days with PM_{10} above EU limit, trim. II	-0.772	-0.001	0.003	-0.001	0.430	-0.004	0.015
	(12.772)	(0.008)	(0.003)	(0.006)	(0.450)	(0.009)	(0.018)
# Days with PM_{10} above EU limit, trim. III	3.689	0.009	-0.003	0.012	0.635	0.009	-0.001
	(19.764)	(0.010)	(0.003)	(0.009)	(0.784)	(0.009)	(0.020)

Notes: Panel A reports the IV estimates of the effect of no. of days with PM_{10} exposure above the EU limit during pregnancy on birth outcomes using the cumulated rain over pregnancy as an instrument; Panel B reports the IV estimates of the effect of no. of days with PM_{10} exposure above the EU limit in each trimester of pregnancy on birth outcomes using the cumulated rain in each trimester as an instrument. Pollution coefficients show the effect of an increase by 10 in days with PM_{10} above EU limit. The unit of observation is the municipality-week-of-birth cell, where the definition of municipality is extended to inclusion of municipalities whose centroid falls within a radius of 15 km from the monitor's geographical coordinates. The estimates are weighted by the number of births in each municipality. Both panels include municipality fixed effects and week-of-birth fixed effects. All controls for maternal and child characteristics are listed in Table 2. Controls also include yearly municipal income as well as average minimum and maximum temperatures during pregnancy (Panel A) or in each trimester (Panel B). Robust standard errors, clustered at the municipality level, are shown in parentheses. Sample size is 13,143 observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix

Table A1: Samples Comparison based on Means

Variable name (SCLB data)	Baseline Sample		Pop. Sample (after restriction)		15km-radius Sample	
	Mean	SD	Mean	SD	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
Birth Weight (grams) (BW)	3272.12	247.97	3270.51	409.06	3273.40	176.53
Low Birth Weight (LBW)	0.05	0.11	0.05	0.18	0.05	0.08
Very Low Birth Weight (VLBW)	0.01	0.04	0.01	0.06	0.01	0.03
Intra-Uterine Growth Restriction (IUGR)	0.02	0.08	0.02	0.13	0.02	0.05
Gestation (days) (GEST)	273.27	6.09	273.04	9.93	273.35	4.38
Pre-Term Birth (PTB)	0.05	0.11	0.06	0.19	0.06	0.08
Low Apgar score (APGAR)	0.03	0.17	0.06	0.19	0.02	0.12
Age of mother	32.28	2.54	31.49	4.28	32.00	1.90
Female birth	0.49	0.25	0.49	0.41	0.48	0.18
Foreign mother	0.19	0.21	0.14	0.29	0.14	0.15
Education (high school)	0.44	0.25	0.46	0.42	0.48	0.19
Education (more than high school)	0.26	0.22	0.15	0.29	0.19	0.15
Dependent employee	0.56	0.26	0.50	0.42	0.58	0.21
Self-employed	0.10	0.15	0.09	0.24	0.09	0.10
Employed mother	0.68	0.24	0.60	0.42	0.68	0.20
Married mother	0.73	0.25	0.76	0.37	0.76	0.18
Previous births	0.45	0.25	0.47	0.41	0.46	0.18
Previous abortions	0.20	0.20	0.17	0.32	0.19	0.14
Type of hospital (private)	0.07	0.17	0.06	0.21	0.07	0.15
Pediatrician (present)	0.58	0.34	0.58	0.44	0.58	0.28

Notes: Baseline Sample: N=12,260; Birth Population Sample (after restriction): N=860,473; 15km-radius Sample: N=13,143. Across samples each cell is made of mothers living in the same municipality and giving birth in the same week of the year. Baseline Sample is our sample of analysis and consists of birth data matched with environmental data, after restrictions and with no missing values. 15km-radius Sample is an extended sample, which includes municipalities whose centroid falls within a radius of 15 km from the monitors' geographical coordinates. Population Sample (after restriction) is obtained after a restriction based on mother's age, singleton birth, gestation age, birth weight, missing values in the relevant variables, and year 2002 due to insufficient environmental data, starting from the overall births population.