Ambient Air Pollution and Pregnancy Outcomes – A Study of Functional Form and Policy Implications

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PRELIMINARY AND INCOMPLETE, PLEASE DO NOT CIRCULATE OR CITE.

Abstract.

We utilize a new data set on ambient air pollution and births from the Salt Lake Valley to study how intensive and cumulative exposure of PM2.5 in the first trimester affect two important pregnancy outcomes - gestational age at birth and the risk of preterm birth. For identification we use variation in cumulative exposure for siblings from the same mother in subsequent pregnancies which can be substantial due to the large seasonal and annual variation in the valley. Controlling for other air pollutants and individual confounders, we find strong evidence of reduced gestational age and increased probability of preterm birth resulting from PM2.5 exposure and estimate that the marginal effects are larger as cumulative exposure increases. We find weak evidence of an increased marginal effect of intensive exposure vs. total exposure. As cumulative exposure plays a larger role than intensive exposure this indicates that policies which decrease average pollution levels can be more effective than policies targeted at peak pollution from a pregnancy perspective.

1. Introduction.

Preterm births have been estimated to account for up to one third of all infant deaths in the United States (Callaghan et.al. 2006) and infants that are born premature have an increased risk of both short- and long-term complications, including difficulties in growth and neurodevelopment (Behrman 2007) which makes understanding the causes and mechanisms behind preterm birth a pressing issue. Maternal factors that have been linked to preterm births include obesity, smoking, advanced maternal age et cetera (see e.g., Räisänen et al. 2013). Exposure to ambient air pollution is an exogenous factor where current research points to significant associations between air pollutants such as PM2.5, CO and NO2 and adverse pregnancy outcomes (Currie et al. 2011; Shah and Balkhair 2011; Stieb et.al. 2012).

In this paper we use 7,224 births of siblings in Utah that occurred between 2009 and 2012 to study the effect of PM2.5 exposure during the first trimester on two pregnancy outcomes defined as gestational age at birth and risk of preterm birth. We contribute to the literature in three distinct ways. First, regulators often combat air pollution by trying to affect population behavior on days with particularly bad air quality. For example, to address air quality problems Utah has defined mandatory action days during days with particularly bad air quality which means that the use of automobiles is discouraged and the burning of wood and coal is prohibited. Paris, France, allowed only cars with even and odd registration numbers to drive in the city every other day during a stint of bad air quality in early 2014. These types of actions have the potential to decrease air pollution problems during bad air quality days. But it might also marginally increase pollution during days after the spell of bad air quality due to individuals postponing wood and coal burning and non-essential trips. Hence, if it is the sum rather than the intensity of exposure during pregnancy that matters for pregnancy outcomes it makes more sense to form policies that decrease average pollution levels for all days rather than focusing on particularly bad air quality days, e.g., policies that move commuters to public transportation from cars for the whole year and not only during bad air quality periods or policies that incentives people to change heating system rather than just banning wood burning during inversions. Second, we use a completely new data set in a region that, to our knowledge, has not been used to study the link between air pollution and adverse pregnancy outcomes. We quantify our findings and estimate the aggregate effect on expected number of preterm births of different reductions in pollution levels. We also discuss different methods to measure the cost to society of ambient air pollution in terms of pregnancy outcomes Third, we discuss some of the technical difficulties that arise when estimating the relationship between ambient air pollution exposure and pregnancy outcomes.

2. Data

The Wasatch Front provides a unique natural experiment for studying the effect of air pollution on pregnancy outcomes since the levels of air pollutants are relatively low for most of the year and high for a relatively short period of time during the annual winter time inversion, during which cold air traps air pollution in the valley for long periods of time (Reeves and Stensrud 2009). We construct exposure variables, as detailed below, and use 7,224 births of siblings in Utah in order to compare births from the same mother at different seasons and years as in for example Currie et al. (2009) or Pereira et al. (2014). We study the effect of PM2.5 levels on two different pregnancy outcomes; gestational age and preterm labor which will also include term babies whose preterm birth was prevented by the use of tocolysis, a medication used to delay preterm uterine contractions thus preventing early birth. As a measurement of ambient air pollution we focus on fine particle matters (PM2.5), but also include exposure to Carbon Monoxide (CO), Nitrogen Dioxide (NO2) and Ozone (O3) as control variables. A detailed discussion on the air quality and birth certificate data follows bellow.

2.1 Air Quality Data

We use air pollution data from the Hawthorne station site at 1675 S. 600 E., Salt Lake City, UT in Salt Lake County, which is the main measuring site in the Salt Lake Valley. Air pollution data were received from the EPA via the EPA datamart. The data are provided to the EPA by the Utah Department of Air Quality. Small gaps of less than 8 days in pollution data did exist for all pollutants except for PM2.5. These small gaps were completed using the average of the prior day and following day of the blank period as in, e.g., Chang et.al. (2012).The gaps amounted to 113 data points out of a total of 5,602, or 2.0%. A larger data gap in Jul-Dec 2010 exists. Births with a gestation period that at some point overlapped with this larger data gap were removed from the analysis.

The data is assumed to be representative of the level of pollution across the valley. The shape of the valley is similar to a frying pan with a leveled valley floor and high mountains surrounding the valley which is the main reason for the winter inversion where hot air acts as a lid and traps the cold air along with pollutants in the valley. A University of Utah study with data from 2011 did measure pollution levels decreasing with increasing elevation. The largest decreases were seen at hilltop levels well above the elevation of most Salt Lake City homes (Silcox et al. 2012). The data available on PM2.5, CO, NO2 and O3 is summarized in table 1:

[Table 1 Here]

To define intensity of exposure we use a health forecast established by the EPA for PM2.5, see table 2 below.

[Table 2 Here]

Levels of PM2.5 range between the levels of “good” and “unhealthy” in the Salt Lake Valley. There are only a few unhealthy for all days every year, no more than 5 annually during our investigated period. There is more variation in the unhealthy for sensitive groups’ data. Those days occur during the winters and for each winter season there are roughly 10 to 20 of those days annually (see also table 3).

2.3 Birth certificate data:

Birth certificate data was provided as de-identified data on 71,504 births for the years 2009-2012 by the Utah Department of Health (UDoH). The information on gestational weeks comes from the clinician’s best estimate of gestational age including data from prenatal and postpartum assessments. For example, a birth on June 3rd, 2010 with a gestation period of 39 weeks had a start of gestation on approximately September 3, 2009 (accurate within one week as gestation period is given in weeks on the birth certificate). We also collected confounding factors from the birth certificates. In our regressions, we control for mother BMI, pre-existing diabetes, asthma, chronic hypertension, infertility drug use, chronic renal disease, heart disease, previous preterm birth, tobacco use, a dummy indicating if the father is different for at least one sibling, maternal age, insurance coverage, adequacy of prenatal care utilization index (see

Kotelchuck 1994 for exact definition) and education. While we don't believe that our confounders are necessarily correlated with pollution, they have been identified as factors that affect gestational age and preterm birth which will help us in identifying the pollution effect.

The initial filters applied to the data by the UDoH were births for mothers with a resident zip code in Salt Lake County. Multiple gestation births (4,403 births in total) were excluded from the birth data. Births were reviewed to ensure that no births with a gestational period of less than 20 weeks or unknown were included, as live births are defined as those of 20 or greater gestational weeks (Alexander et al. 1996; Behrman 2007). Births were also reviewed to ensure that no births with an unrealistic weight for reported gestational age were included, as these suggest errors in birth certificate data (Alexander et al. 1996).

The main restriction of our final sample is that it only includes mothers that had two or more full gestation periods during our period of study. A coded parameter for parents' social security numbers (SSN) was included in the birth certificate data. Using this field, siblings were identified based on common maternal SSN and we could identify full and half siblings with the help of father SSN. Infants with parents where one or both SSN's were missing were removed from the analysis. We also removed births to a few mother where the reported ethnicity had changed between births as we assume that the information provide in these birth certificates was of lower quality. This method produced a sample of 7,224 live births to 3,600 mothers with complete air quality data available. A statistical summary of our outcome variables together with our main independent variables is presented in table 3 below.

[Table 3 Here]

3. Identification strategy.

Exposure is to some extent endogenous. To overcome this, earlier studies have used data from several measuring stations and compared individuals across different stations that live within a certain distance while controlling for confounding factors such as ethnicity and education (Le et al. 2012; Huyn et al. 2006). There is still, however, the problem of unobserved factors that could be correlated with pollution exposure and pregnancy outcomes. For examples, wealthy families might live in areas with less pollution and have greater flexibility to leave or remain indoors during periods of significant pollution and also have the ability to invest in measures that improve pregnancy outcomes such as high quality prenatal care. To address this endogeneity problem, recent papers, such as Currie et al. (2009) and Pereira et al. (2014), compare siblings born by the same mother, so that variation in exposure for the same mother is used for identification, a strategy that also we adopt with some amendments. Compared to these earlier studies, the biggest advantage of using data from the Salt Lake Valley is that we utilize time variation in exposure rather than spatial variation since the pollution levels vary heavily in the Salt Lake Valley between seasons (primarily due to winter time inversions) and also between years. A pregnant woman is always exposed to some level, which means that even if she plans her pregnancy to avoid the inversion season, she will still be exposed to different levels of pollution during the different pregnancies and contribute to identification.

We have two outcome variables, gestational age at birth (in weeks) and preterm birth defined as a birth taking place before the 37^{th} week or a term birth that included the use of tocolysis. For gestational age we are interested in the parameter α in the following model

$$ga_{in} = \alpha PM2.5_{in} + P_{in}\beta + X_{in}\gamma + M_i + T_n + \varepsilon_{in} \quad (1)$$

where *i* and *n* indexes mother and birth order, ga_{in} is the outcome, $PM2.5_{in}$ is first trimester exposure of PM2.5 defined as the sum of daily average exposure, P_{in} is a vector of the aggregate pollution levels of the three other pollutants in the first trimester, X_{in} is the vector of confounders defined in the previous section, M_i and T_n are mother and time (yearly and quarterly) fixed effects respectively and ε_{in} is an error term containing a mother specific fixed component (a_i) potentially correlated to PM2.5 exposure ($\varepsilon_{in}=a_i+e_{in}$ where is a e_{in} common i.i.d. error term). Since the specification of equation 1 is linear, we can estimate the parameters of interest by using a within transformation to absorb the unobserved mother fixed effects.

Since it is likely that pollution in the first term period is correlated with pollution in the second and third term period we need to control for this. Controlling for the total amount of pollution may be misleading as preterm babies will have shorter pre natal exposure than term babies. Hence, we control for average weekly pollution levels for all four pollutants between the first trimester and time of birth.

We define the preterm birth outcome as 1 if birth is term and 0 if birth is preterm. Hence a negative marginal effect of a variable implies an increase in the risk of preterm birth (hence, a negative marginal effect is “bad” for both our gestational age and preterm outcome). With preterm being a binary outcome variable we can use a linear probability model (LPM) using within transformation to estimate the regression parameters. However, linear probability models display several weaknesses such as linear marginal effect and possibly predicted outcomes outside the unit interval. The usual way to address this is by using non-linear probability models such as the logit model which has been used extensively in this literature. The problem with the logit model is that due to the non-linearity, a simple within transformation cannot be used to control for mother fixed effects. The simplest approach to address the endogeneity problem without using within transformation is to try and control for observable confounding factors as in e.g., Llop et al. (2010) but this method can never control for intrinsic, unobserved mother specific effects. A straightforward approach to do this is to actually estimate the mother fixed effects by including a set of dummies as in Currie et al. (2009). However, using a logit model combined with panel data and with only a few births per mother, we encounter the incidental parameters problem which may cause both bias and inconsistency in our estimates (Lancaster 2000). Neither of these approaches is entirely satisfying for this particular setting. Hence, we use logit models without and with fixed effects, LPM models on within transformed variables and as a final robustness test, we estimate a conditional logit model (CLM) which essentially is a within transformation for a logit model avoiding the incidental parameters problem while still being able to use the panel feature (Chamberlain 1980). CLMs have been shown to perform well in for example estimating labor supply elasticities (Haan 2006). The drawback with using a CLM is that only mothers that have had at least one preterm birth will be used in estimation which will mean that predicted probabilities are conditional on having at least one preterm birth. Hence we only use the CLM for additional robustness test and use the LPM to estimate predicted effect of reducing air pollution.

It should also be mentioned that another way to address the problem is to use random effects as in Pereira et al. (2014). The underlying assumption that justifies the use of random effects is that the covariates should be unrelated to unobserved specific constants, the assumption we are trying to address from the very beginning.

To study if the marginal effects differ for different levels of pollution we use linear, polynomial and log specifications, in both the linear and the non-linear models. To study if intensive pollution has a particularly large effect on pregnancy outcomes we add the number of days during the first trimester where air quality was considered to be unhealthy for sensitive groups and unhealthy for all by including count variables representing the number of days PM2.5 levels have exceeded the thresholds defined in table 2. Thus, we will see if there is an additional marginal effect of those particularly bad air days in addition to the cumulative exposure of air pollution a mother has experienced during her first trimester.

4. Results.

The estimated coefficients from a range of specifications are presented in the appendix in table A1 using gestational weeks and the outcome variable and table A2 using preterm birth as a binary outcome variable. Standard errors are clustered throughout on the mother in all specifications except for the first column in table A1 and table A2 which does not utilize the panel structure and are shown for comparison. A quadratic, concave relationship was shown to be the best fit for all pollutants (higher order polynomials did not improve fit and were not significant) for both gestational weeks and the preterm outcome. The average marginal effect of PM2.5 is, as expected, consistently estimated to be negative across all specification for both outcome variables, that is, both expected gestational age and chance of term birth decreases in PM2.5 levels.

To quantify the relationship between PM2.5 and the outcome variables, we use the specifications from columns 3 and 3 from tables A1 and A2 and present two graphs below that show the marginal effect on gestational age and chance of term birth from an increase in 10 units of PM2.5 exposure (about 3% of a standard deviation) in the first trimester across a range of different exposure levels.

[Figure 1a and 1b here]

For comparison, the linear estimates from columns 2 in table A1 and A2 are represented by the dotted green line in each figure; a decrease in 0.013 weeks or 0.091 days in gestational age and a decrease in chance of term birth by 0.1 percentage point (pp) due to a 10 unit increase in PM2.5 exposure respectively. The marginal effects from the quadratic specification are shown for different levels of exposure. The larger the cumulative level of exposure, the more negative is the marginal effect of a 10 unit increase of PM2.5 on both outcomes. For low levels of exposure, there is a slight positive effect on both outcomes. We do not believe that this represent a true positive causal effect on gestational age or chance of term birth but rather that it is an artefact of the larger negative effect of the higher exposure levels (estimating the regression using only observations in the lowest tertile, the relationship between PM2.5 and gestational weeks is negative but statistically weak). Converting the effects on weeks into days, for levels of exposure equal to 800, 1,100, and 1,550 PM2.5, adding 10 units of PM2.5 exposure is predicted to reduce gestational age at birth by 0.03, 0.19, and 0.42 days respectively. For the same levels of exposure, adding 10 units of PM2.5 exposure is predicted to decrease the chance of term birth (increase the risk of preterm birth) by 0.004, 0.2, and 0.6 pp respectively. These effects are not only statistically significant but also large in terms of real world impacts.

We find little evidence of any additional effect of peak day exposure, see column 4 and 5 in table A1 and columns 5 and 6 in table A2 in the appendix. Once controlling for mother fixed effects only unhealthy sensitive days are marginally significant in one specification. Our results indicate that there might be an increase in the absolute value of the marginal effect on gestational weeks of intensive exposure. However, the effect is estimated to be small in a real world sense and more data and further studies are needed for more precise results.

For the preterm outcome we see that the results carry over nicely from the LPM model with fixed effects and the logit model to the CLM. The shape of the relationship with preterm is similar to gestational weeks. We get similar result in terms of extensive exposure once controlling for the cumulative amount. Addressing the mother fixed effects using a CLM does not seem to alter any of the lessons learned from our alternative specifications, the LPM using within estimation or the logit model with fixed effects. Although we cannot be sure that this would hold also for earlier studies this result does not discredit any earlier research papers that in some way use within mother variation.

We use two different methods to quantify the effect of pollution. First we predict the number of preterm births using our estimated result from column 3 in table A2. We then calculate the standard deviation of PM2.5 exposure in the first trimester separately for each birth month. We then subtract a tenth of this monthly standard deviation from the actual first trimester exposure for each individual (for reference, a tenth of a standard deviation is roughly 2-3 % of average first term exposure). If a predicted probability is outside the unit interval, we restrict it to be 1 (none is less than zero). We then predict the number of preterm births with the new variable values of PM2.5. This means that exposure is reduced all year around. Our second method reduces exposure only during winter inversions. We predict the number of preterm births given that there was no winter inversion season. More specifically, for mothers that give birth in July, August and September (mothers who have the first trimester during the winter inversion season) we assign a value of first trimester PM2.5 exposure equal to the yearly average, excluding the inversion months. We then compare the number of estimated preterm births to the original estimate using method 1. We make the further assumption that a reduction in PM2.5 exposure can never increase the probability of a preterm birth, any such changes are restricted to be 0. The results are presented in table 4.

[Table 4 Here]

The effect of reducing PM2.5 year around is predicted to generate significant effects. When PM2.5 is decreased by a tenth of a monthly specific standard deviation, the number of preterm birth is predicted to decrease by 1.9%. In our entire sample of Salt Lake Valley births there are 4987 preterm births, or approximately 1247 annually. If we assume that the estimated coefficients are representative of also this sample (there is nothing decisively different between mothers who gave birth 1 time or more times between 2009 and 2012) the results indicate that there would have been about 23 fewer preterm births annually with a 0.1 monthly standard deviation reduction in PM2.5. When we assume no winter inversion the effects are much larger. We now predict a decrease of 10.3 % in preterm births or every 10th preterm birth could be avoided by bringing down PM2.5 to spring, summer and fall averages. Assuming that the results would hold for the entire sample would mean that 125 preterm births annually could be avoided. However, these results should be interpreted with great care as we the reduction in exposure is more than just marginal using this method. We also want to add that we do not necessarily believe that this decrease in pollution levels would be feasible.

5. Discussion

We estimate strong associations between PM2.5 and pregnancy outcomes. We do not find strong evidence that intensity of exposure matters. We consistently estimated the effect of intensive exposure to be negative but the estimates were not statistically significant, possibly due to small variation. More importantly, we find that the marginal effects are the largest for high levels of cumulative exposure. Hence we believe that regulatory actions that aim to reduce average pollution are, from a pregnancy perspective, potentially even more important compared to policies that address pollution only during particularly bad air quality days. Regulatory actions during bad air quality days should be complemented by actions that make sure that pollution peaks are not smoothed out to later days since we cannot reject that for a given exposure level, the marginal effect is the same regardless of how intensive exposure is. One example of this policy trade off would be to provide grants for people to change their heating system from wood burning rather than just banning wood burning during bad air quality periods. Temporal effects are also important. During late fall (the period prior to the winter inversion season in the Wasatch Front) days with air quality that are classified as good but close to moderate are the first building blocks for expected high cumulative exposure. Since our results point towards that it is the cumulative effect that matters policies should be considered that curb pollution levels also during late fall and not only during the inversion season.

The most significant limitations on the study is the time period (birth certificate data in the same format are available only from 2009 to present) and the lack of knowledge on mother's habits during pregnancy as well as the assumption of consistent exposure regardless of home or work proximity to highways or other pollution sources. Some examples of this variation can be as simple as a mother who works in a restaurant kitchen or at a mine or construction site with increased particulate matter exposure. Previous studies have attempted to control for this via a proximity range around the measuring site, though results for those within the proximity vs. those at a greater distance did not show great difference (Le et al. 2012). Home proximities to highways or other industrial areas can certainly create pockets of higher pollution than the assumed average for the Salt Lake Valley based on the Hawthorne measuring site. An analysis of air quality across different elevations in the Salt Lake Valley confirms that different valley locations have different pollution levels (Silcox et al. 2012). It is today not possible to measure exposure at a more individual level. The parent fixed effects should to some extent address the endogeneity problem unless there is a strong correlation between mother characteristics and moving to more or less heavily polluted areas during particularly bad years.

An important consideration in any discussion of the policy implications of a matter such as this, is the costs of not addressing air quality compared to the cost of addressing it. First of all, efforts to improve air quality will not only have a positive effect on pregnancy outcomes but also benefits individuals in other “high-risk” groups including those with asthma, cardiovascular disease, lung disease, etc. However, even if we restrict the cost discussion to preterm births we have a problem in estimating the total cost due to the distributional effects of preterm birth. An infant that is born extremely premature is associated with extra costs in the region of $10,000 a-day while in the intensive care unit and be at much greater risk for long-term complications. An infant born late pre- term and early term may incur additional cost to that of a term infant as the low gestational age may prevent lower- cost midwifery care, increase the use of prophylactic medications other interventions, and require treatment at tertiary care facilities, but these costs are much lower than an early preterm infant. We treat preterm as a binary outcome so our estimate reflects only how many more preterm infants there will be in aggregate. However, we also expect infants that are already preterm to have a lower gestational age but this is an effect we cannot measure. It is important to remember that even for the most affected mothers the expected outcome is a term birth so we cannot use gestational age as a measure. Another alternative would be to classify preterm births in different categories depending on how preterm they are, however our limited data has too few data points in the lowest categories so a much larger data set is needed for estimating costs using this approach. A simple option to calculate costs would be to take the naïve approach and estimate an average cost for a preterm baby disregarding distributional effects. Behrman, et al, (2007) reports a comprehensive estimate of an average increased cost of $61,000 (in 2014 health care dollars) per preterm infant (see also Soilly et.al 2014). This would imply that improving air quality during the winter would lead to an estimated cost saving of $7,625,000 or $478 if that sum is averaged across each single birth in a year. However, these numbers should be treated with caution and should serve as indicators that much more research is needed to understand the true cost. For example, it does not take into account any distributional effects or the emotional stress a preterm birth can cause for a family, a cost that is in general not even quantified when we discuss costs of preterm birth.

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Appendix:

[Table A1 and A2 Here]

6. References:

Alexander GR, Himes JH, Kaufman RB, Mor J, Kogan M (1996) A United States national reference for fetal growth. Obstetrics and Gynecology. 87(2):163-8.

Behrman R, Butler A (2007) Committee on Understanding Premature Birth and Assuring Healthy Outcomes. Preterm birth : causes, consequences, and prevention. Washington, D.C.: National Academies Press.

Callaghan W M, MacDorman M F, Rasmussen SA, Qin C, Lackritz EM (2006) The Contribution of Preterm Birth to Infant Mortality Rates in the United States. Pediatrics. 188(4):1566-1573.

Campen J, Lund A, Rosenfeld M (2012) Mechanisms linking traffic-related air pollution and atherosclerosis. Current Opinion in Pulmonary Medicine. 18(2):155–160.

Chang H, Reich B, Miranda L (2012) Time-to-Event Analysis of Fine Particle Air Pollution and Preterm Birth: Results From North Carolina, 2001–2005. American Journal of Epidemiology. 175(2):91-98.

Chamberlain G (1980) Analysis of Covariance with Qualitative Data. Review of Economic Studies 47: 225-238.

Currie J, Heep Ray S, Neidell M (2011) Quasi-experimental studies suggests that lowering air pollution levels benefits infants' and children's health. Health Affairs 30(12):2391-2399.

Currie J, Neidell M. Schmeider J (2009) Air Pollution and Infant Health: Lessons from New Jersey. Journal of Health Economics.28:688-703.

Haan P (2006) Much Ado About Nothing: Conditional Logit vs. Random Coefficient Models for Estimating Labor Supply Elasticities. Applied Economic Letters. 13(4):251-256.

Huynh M, Woodruff TJ, Parker JD, Schoendorf KC (2006) Relationships between air pollution and preterm birth in California. Paediatric and Perinatal Epidemiology. 20:454-461.

Kotelchuck, M (1994) Overview of Adequacy of Prenatal Care Utilization Index; Department of Maternal and Child Health. American Journal of Public Health. 84(9):1486-1489.

Lancaster T (2000) The Incidental Parameter Problem since 1948. Journal of Econometrics. 95(2):391-413.

Le H, Batterman S, Wirth J, Wahl R, Hoggatt K, Sadeghnejad A, Hultin M, Depa M (2012) Air pollution exposure and preterm and term small for gestational age births in Detroit, Michigan: Long-term trends and associations. Environment International 44:7-17.

Llop S, Ballester F, Estarlich M, Esplugues A, Rebagliato M, Iniguez C.(2010) Preterm birth and exposure to air pollutants during pregnancy. Environmental Research 110:778-785

Pereira G, Belanger K, Ebisu K, Bell M (2014) Fine particulate matter and risk of preterm birth in Connecticut in 2000-2006: A longitudinal study. American Journal of Epidemiology 179(1):67-74.

Pope A, Dockery D (2006) Health Effects of Fine Particulate Air Pollution: Lines that Connect. Journal of the Air & Waste Management Association. 56:709-742.

Reeves HD, Stensrud DJ (2009) Synoptic-scale flow and valley cold pool evolution in the western United States. Weather Forecasting. 24:1625-1639.

Räisänen, S., Gissler, M., Saari, J., Kramer, M.,and Heinonen, S (2013) Contribution of Risk Factors to Extremely, Very, and Moderately Preterm Births – Register-Based Analysis of 1,390,742 Singleton Births. PLoS ONE, 8(4), doi:20.1371/journal.pone.0060660.

Shah P, Balkhair T (2011) Air pollution and birth outcomes: A systematic review. Environment International 37:498-516.

Silcox G, Kerry K, Crosman E, Whiteman D, Allen B (2012) Wintertime PM2.5 concentrations during persistent, multi-day cold-air pools in a mountain valley. Atmospheric Environment 46:17-24.

Soilly AL, Lejeune C, Quantin C, Bejean S, Gouyon, JB (2014) Economic analysis of the costs associated with prematurity from a literature review. Public Health 128:43-62.

Stieb D, Chen L, Eshoul M, Judek S (2012) Ambient air pollution, birth weight and preterm birth: A systemic review and meta-analysis. Environmental Research 117:100-111.

Tables

Table 1: Salt Lake City (Hawthorne Station) Air Quality Data

Pollutant	**Variable definition**	**EPA Datamart**	**Supplemental Data (gaps < 8 days)**	**Total Datapoints**
CO	Daily Max 8-hour Concentration	1582	61	1643
NO2	Daily Max 10-hour Concentration	1609	34	1643
Ozone	Daily Max 8-hour Concentration	655	18	673
PM2.5	Daily Mean Concentration - ug/m3 LC	1643	0	1643
Total of all pollutants		**5489**	**113**	**5602**

Note: *Number of observations on each of the pollutants between 2009 and 2012. For each birth the observations are then summed over all observations during the first trimester.*

Table 2: Air Quality Index, classification of days based on 24-hour average PM 2.5 levels

Air Quality Index (AQI)	**PM 2.5**
Good	0-12 μg/m^3
Moderate	12.1-35.4 μg/m^3
Unhealthy for Sensitive Groups	35.5-55.4 μg/m^3
Unhealthy All	55.5-150.4 μg/m^3
Very Unhealthy	150.5-210.4 μg/m^3
Hazardous	Above 210.5 μg/m^3

Note: *Each day is assigned a classification based on the 24-hour average PM2.5 levels. AQI sourced from Utah Department of Air Quality.*

Table 3: Descriptive Statistics on outcome variables and pollution data

Variable	**Sibling Sample (N=7,224)**			
	Mean	S.D.	Min	Max
PM2.5	734.5	301.8	313.8	1825.9
Unhealthy Sensitive	0.8	2.3	0	15
Unhealthy all	0.3	1.1	0	4
Gestational Weeks	38.6	1.6	21	42
		Count	**%**	
Preterm or Tocolysis	Yes	512	7.1	
	No	6,712	92.9	

Note*: Descriptive statistics of dependent variables and PM2.5 exposure, number of days in the Unhealthy for sensitive groups category, and the Unhealthy category.*

Table 4: Estimated effects of pollution reduction

	Original prediction	Prediction after pollution reduction	Reduction in %
0.1 monthly s.d. reduction	580	569	1.9 %
No winter inversion	580	520	10.3%

Note: *Predicted number of preterm births using the estimates in column 2, table 6. Row 1 shows before and after a monthly specific 0.1 standard deviation reduction in first term exposure to PM2.5. The second row shows the reduction in estimated preterm births assuming exposure for mothers that give birth in July August or September has a first trimester exposure level equal to the average of the rest of the year.*

Table A1: Gestational weeks within estimation

VARIABLES	(1) Gest. Weeks	(2) Gest. weeks	(3) Gest. Weeks	(4) Gest. Weeks	(5) Gest. Weeks
PM2.5	0.005517***	-0.0012985***	0.005548***	0.005831***	0.005523***
	[5.71]	[-2.93]	[5.06]	[5.21]	[4.96]
$PM2.5^2$	-0.000004***		-0.000004***	-0.000004***	-0.000004***
	[-7.20]		[-6.38]	[-6.40]	[-5.84]
Un. sens. days				-0.046280	
				[-1.74]	
Unhealthy days					-0.009960
					[-0.126087]
Other pollutants	Yes	Yes	Yes	Yes	Yes
Average Exposure Until Birth	Yes	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes	Yes
Confounders	Yes	Yes	Yes	Yes	Yes
Within estimation	No	Yes	Yes	Yes	Yes
Observations	7,224	7,224	7,224	7,224	7,224

Note: *Clustered t-statistics in brackets. *** p<0.001, ** p<0.01, * p<0.05. Outcome variable is gestational weeks and column 2-5 uses mother F.E. Standard errors are clustered on the mother.*

Table A2: Pre or Toco within estimation

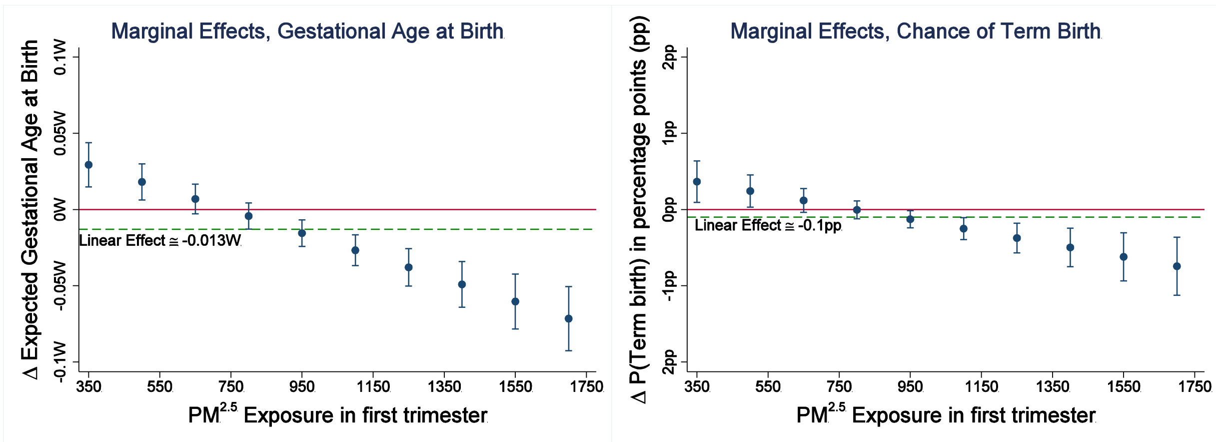
VARIABLES	(1) Term Birth	(2) Term Birth	(2) Term Birth	(3) Term Birth	(4) Term Birth	(5) Term Birth
PM2.5	0.015115***	-0.000100*	0.000653**	0.015602***	0.000717***	0.000626**
	[5.89]	[-1.76]	[3.041]	[3.84]	[3.30]	[2.78]
$PM2.5^2$	-0.000010***		-0.000000***	-0.000011***	-0.000000***	-0.000000**
	[-7.01]		[-3.56]	[-4.78]	[-3.54]	[-2.91]
Un. sens. days					-0.010438*	
					[-2.37]	
Unhealthy days						-0.010618
						[-0.857039]
Other pollutants	Yes	Yes	Yes	Yes	Yes	
Average Exposure Until Birth	Yes	Yes	Yes	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Confounders	Yes	Yes	Yes	Yes	Yes	Yes
Within Estimation	No	Yes	Yes	Yes	Yes	Yes
Clogit	No		No	Yes	No	No
Observations	7,224	7,224	7,224	637	7,224	7,224

Note: *Clustered z- and t-statistics in brackets. *** p<0.001, ** p<0.01, * p<0.05*. *Outcome variable is term birth. Column 1 is a logit without mother F.E. Columns 2 and 4-5 is a LPM model with mother fixed effects. Column 3 is the CLM model. Standard errors are clustered on the mother*

Figures

Figure 1

a b



Note: Estimated marginal effects of a 10 unit increase in PM2.5 on gestational age at birth (a) and chance of term birth (b).