Prenatal Exposure to Air Pollution and Infants' Health Outcomes in the US*

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Abstract

This paper studies the impact of air pollution on birth outcomes in the US over several decades. We employ roughly 70 million birth records observed over the years 1980 to 2020. Our identification strategy exploits within-county-month and within month-year of birth variations in exposure to precipitation-induced changes in air pollution. We find negative and large effects on a wide range of birth outcomes. Our findings suggest that a one-standard-deviation rise in ozone is associated with a 6.4 and 12.8 percent rise in the share of low birth weight and very preterm birth infants with respect to the mean of the outcomes. Further analyses suggest that these effects are heterogeneous across trimesters of pregnancy and reveal larger impacts during second and third trimesters.

Keywords: Air Pollution, Birth Outcomes, Infant Health, Precipitation

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1. Introduction

It is well documented that the period of prenatal development is a critical period for infants' health outcomes (Almond et al., 2011; Currie et al., 2009; Currie and Schwandt, 2016; Lindo, 2011; Noghanibehambari, 2022; Rocha and Soares, 2015). The primary hypothesis is the influence of external stressors on fetal development and the subsequent changes in epigenetic programming that result in deteriorations in physiological growth (Almond and Currie, 2011; Barker et al., 2002). A strand of this literature evaluates the detrimental effects of air pollution on infants' health outcomes (Argys et al., 2021; Arroyo et al., 2016; Franklin et al., 2019; Sanders, 2012; Shah and Balkhair, 2011). Based on the fetal origin hypothesis, pollution operates as an environmental trigger and sends a signal to the reproductive system of the mother. This information changes the epigenetic codes and causes a process called *methylation*, in which some methyl molecules are attached to specific parts of DNA and silence-off some growth-related genes. The main purpose of this gene regulation is to increase the chances of survival. However, this epigenetic programming change results in lower tissue growth and degenerated organ development and can be detected in lower initial health endowment at birth, including lower birth weight and lower gestational age (Altindag et al., 2017; DeCicca and Malak, 2020; Hill, 2018; Inoue et al., 2020). Indeed, several studies show that prenatal exposure to pollution is associated with negative health outcomes for infants (Coneus and Spiess, 2012; Huang et al., 2015; Luechinger, 2014; Pons, 2022). Our paper joins this literature by providing evidence of the effects of air pollution on birth outcomes using a large panel of individuals observed over the years 1980-2020.

The contribution of the current research to the ongoing research on the negative health effects of air pollution is twofold. As opposed to many studies that employ ordinary least square (OLS) strategies and work with cross-sectional estimates (Shah and Balkhair, 2011), we apply a new method to exploit the exogenous within count-month variations in air pollution. Second, previous research usually focuses on a specific geographic area or limited time period (Currie et al., 2009; Currie and Neidell, 2005; Gonzalez et al., 2020, 2022; Lee et al., 2013). This paper employs birth data from many counties across US states and over 41 years (1980-2020). The more comprehensive data allow for wider variation in air pollution and also makes the estimates more representative of the US population.

The rest of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 discusses data sources, sample selection, and the empirical method. Section 4 reviews the results. We conclude the paper in section 5.

2. Literature Review

There is a relatively large literature that examines adverse health effects of pollution on a wide array of health outcomes including infants' health outcomes (Argys et al., 2021; Arroyo et al., 2016; Bergstra et al., 2021; Cushing et al., 2020; Franklin et al., 2019; Gray et al., 2014; Ha et al., 2014; Huang et al., 2015; Inoue et al., 2020; Lavigne et al., 2016; Lee et al., 2013; Liu et al., 2022; Mahanta et al., 2016; Malmqvist et al., 2011; Shah and Balkhair, 2011; Strand et al., 2011; Tsurumi and Managi, 2020). For instance, Pons (2022) argues that the mean effects of air pollution on birth outcomes produced by OLS regressions do not provide the full image of the adverse effects as some infants might be at much higher risks. She employs grouped quantile regressions and shows that the negative effects on birth weight among infants at the first and second deciles of conditional distribution are several times larger than those at the median of the distribution. Bartik et al. (2019) explore the association between local traffic congestion and weekly infant mortality rates. They construct instruments based on traffic congestion and weather conditions and find significant effects of air pollution on infant mortality rates with the largest effects from carbon monoxide. Currie et al. (2009) use data from California and employ mother fixed effects and explore the association between maternal exposure to criteria air pollution during pregnancy and infants' birth outcomes. They find negative effects specifically for second and third-trimester exposure to ozone, carbon monoxide, and PM10. DeCicca and Malak (2020) explore the impact of the Clean Air Interstate Rule (CAIR) that stipulated reductions in power plant emissions in the eastern United States. They find that policy-induced reduction in particulate matters improved birth outcomes among older mothers and those considered clinically-designated risky pregnancies.

Gehrsitz (2017) evaluates the effects of low emission zone policies that were adopted in several cities in Germany. He finds that the policies had a modest effect on air pollution at a city's highest-polluting monitor. However, he fails to find any meaningful effects of the policy-driven reductions in air pollution on infants' health outcomes. Altindag et al. (2017) explore the impact of yellow dust outbreaks, a natural phenomenon that brings clouds of pollution from China and Mongolia to Korea, on birth outcomes. They find that despite public alerts and potential individual avoidance behavior the outbreak of yellow dust during pregnancy is associated with lower birth weight and gestational age. Coneus and Spiess (2012) use data from Germany and show that high exposure to air pollution is associated with roughly 290 grams lower birth weight. Currie et al. (2017) and Hill (2018) explore the effect of shale gas development during the post-2000 years in Pennsylvania on air pollution and birth outcomes. Both studies employ a similar empirical method using birth record data and find that drilling-induced rises in air pollution are associated with negative birth outcomes. Rangel and Vogl (2019) employ data from vital statistics of Brazil and explore the effects of agricultural fires on infants' health outcomes. They find that sugarcane harvest fires emit large amounts of pollutants into the air and negatively affect birth outcomes of mothers in their late pregnancy. Currie and Schwandt (2016) explore the impact of pollution from dust clouds created after the 9/11 terrorist attacks on birth outcomes. They find significant effects on low birth weight and preterm birth.

3. Method

3.1. Study Population

The primary source of data is county-identified restricted-access vital statistics birth records extracted from National Center for Health Statistics (NCHS) for the years 1980-2020. The data covers the universe of birth records in the US and provides information on several birth outcomes as well as limited information on parental characteristics. It reports each record's gender, birth weight, gestational age, Apgar score, and year-month of birth. The data also contain the mother's race, ethnicity, age, smoking status, education, and marital status. There is also limited information about the father including age and race.

We also restrict the sample to mothers of at least 15 years old and at most 45 years old since births out of this age range are highly uncommon, and their outcomes could have been strongly driven by age-related factors. Finally, we restrict the sample to the years 1980-2020 since both birth data and air pollution data are more comprehensive for post-1980 years.

3.2. Exposure Measures

Air pollution data comes from daily pollution reports of the Environmental Protection Agency (EPA). The data is monitor-based and reports various pollutant measures on a daily basis. However, not all monitors report all pollutants, and not all monitors that report a specific pollutant do so on a regular basis. This irregularity in measuring the pollutant varies across monitors and time. Moreover, there are place-time differences in measuring and reporting pollutants. For instance, Grainger and Schreiber (2019) show that monitors systematically avoid measuring pollutants in periods of hotspots and that this discriminatory behavior is correlated with counties' demographic characteristics. Local regulators avoid pollution hotspots in poorer counties and counties with a higher share of blacks. Therefore, the resulting measurement error generates a bias in OLS regressions since the error is correlated with other determinants of birth outcomes including socioeconomic characteristics. This issue is inherent in studies that exploit observational pollution measures. To mitigate this problem, we restrict our analysis to a subset of counties and a subset of pollutants. We focus on two important and widely reported measures: Ozone and PM10 (Particulate Matters less than 10 μm). We restrict the pollution data to counties that reported these pollutants every month of the year and did so for all months in a given year. This results in a subset of 1,270 counties.[6] Figure 1 shows the geographic distribution of these counties across the US. There are more counties in West and Northeast regions in the final sample. This brings two concerns in our sample selection and study population. First, there are more major cities and urban residents in these regions. One may truly argue that the presence of more urban individuals in the sample could confound the estimates if the effects of air pollution on birth outcomes are different based on urbanicity. We explore this concern in Appendix E and show that in our final sample the effects are relatively similar in urban versus non-urban areas. Second, one could also be concerned about differences in characteristics of individuals in the final sample versus those that are excluded due to unavailability of data. We explore this issue in Appendix B. We show that, relative to the original sample for which we have not yet imposed any sample selection due to data unavailability, the final sample covers more educated parents and higher income counties. We then show that the main results of the paper are indeed larger among subsample of low educated parents and low income counties. Therefore, the results of the paper could be larger for the excluded observations.

[6] Appendix A provides a list of the counties in the final sample.

The EPA data is at the monitor-level and daily-frequency. We use all monitors within a county boundary to aggregate the data at the county-level and monthly-frequency. In so doing, we employ county population as the aggregation weights.[7] We then merge the pollution data with the NCHS birth data based on the prenatal exposure period. In so doing, we use the information on month-year of birth and gestational age to determine months of pregnancy. We then assign average county-by-month values of pollution to each birth record's months of the prenatal period. Finally, we aggregate all prenatal pollution exposure by averaging the assigned pollution values throughout the in-utero period. For instance, for a baby that is born in December with 9 months of gestation, we use average county-month pollution values over the months of April-December.

3.3. Atmospheric Measures

We also employ county-level temperature, humidity, and precipitation data extracted from Global Surface Summary of the Day data files provided by the National Oceanic and Atmospheric Administration (NOAA). The NOAA dataset reports the exact location of each station. We use the longitude and latitude of county centroid in order to map stations across counties. We employ three strategies to assign values to each county. First, if there is one station in the county, we use the value reported by that station. Second, if there are more than one station in the county, we average all values using county population as weights. Third, if there is no station in the county, we use the average value of all neighboring counties for which steps one and two works. If none of the neighboring counties has any value in steps one and two, then we assign a missing value to that county. Finally, similar to pollution data, we aggregate the NOAA dataset at the month-year (by

[7] In Appendix F, we show the validity of our final air pollution exposure by documenting a strong and robust association between the final sample's pollution measures and the daily-by-monitor pollution measures for the same set of counties that appear in the final sample.

county) level and assigned it during months of the in-utero period. Figure 2 illustrates the statistical distribution of ozone and PM10 concentration through a series of boxplots.

3.4. Constructing Final Sample

We collapse the final sample at the county-month-year-gender-race level. The number of pre-collapse individual observations is 69,936,360. Table 1 reports summary statistics of the final sample. Roughly 7.2 percent of births are categorized as low birth weight (i.e., having a birth weight of less than 2,500 grams). The average gestational age is 38.8 weeks. The average prenatal exposure to PM10 is 22.9 micrograms per cubic meter (hereafter $\frac{\mu g}{m^3}$). The average ozone exposure is 28.6 $\frac{\mu g}{m^3}$. To ease the interpretation of results, we standardize pollution measures and atmospheric measures.

In further analyses, we also employ county-level sociodemographic data from several sources. Data on population composition comes from SEER (2019). Income data is extracted from the Bureau of Economic Analysis. Average industry wage and industry-specific employment data come from the Quarterly Census of Employment and Wages.

3.5. Statistical Method

Our econometric method compares birth outcomes of mothers in county-months that were exposed to higher/lower levels of air pollution due to inter-county-month variation in precipitation. Specifically, we employ the following two-stage-least-square estimations:

$$P_{cmtrg} = \alpha_0 + \alpha_1 PRCP_{cmt} + \alpha_2 X_{cmtrg} + \alpha_3 W_{cmt} + \zeta_{cmtrg} + \varepsilon_{cmtrg} \quad (1)$$

$$y_{cmtrg} = \alpha_0 + \alpha_1 P_{cmtrg} + \alpha_2 Z_{cmtrg} + \alpha_3 V_{cmt} + \xi_{cmtrg} + \epsilon_{cmtrg} \quad (2)$$

The data is aggregated into county (c), month (m), year (t), child's race (white/non-white, r), and child's gender (male/female, g). In this formulation, P is standardized pollution measure (ozone and PM10). In equation 1, the parameter $PRCP$ represents standardized values of precipitation. The parameter y represents the birth outcome of each child. We focus on seven outcomes that are discussed below. *Birth weight* is the child's weight at birth measured in grams. *Low birth weight* is a dummy that indicates whether the child's birth weight is less than 2,500 grams. *Very low birth weight* is a dummy that equals one if the child's birth weight is less than 1,500 grams and zero otherwise. *Full-term birth weight* is the birth weight of infants who reach maturity in their prenatal period, i.e., birth weight of those with gestational age between 37-42 weeks. *Fetal Growth* is the average weekly growth of infants during their gestational period, i.e., birth weight divided by gestational weeks.[8] *Gestational age* is a clinical estimate of the period between the first day of a woman's last menstrual period to the day of birth. *Very premature birth* is a dummy that equals one if the gestational age is less than 28 weeks and zero otherwise.

To account for differences in birth outcomes among families of different sociodemographic backgrounds, we include a series of average cell-level parental controls in X and Z in the first stage and second stage, respectively. These controls include mother's race (three categories), mother's ethnicity, mother's age, mother's education (six categories), mother's having any prenatal visits, and father's age (eleven categories).

A relatively large strand of research suggest that temperature and humidity have direct impacts on birth outcomes (Bachwenkizi et al., 2022; Basagaña et al., 2021; Chen et al., 2020; Grace et al., 2015; Hajdu & Hajdu, 2021; McElroy et al., 2022; Molina & Saldarriaga, 2017;

[8] There are two reasons that justify using fetal growth in our analysis. The literature suggests that this measure better captures infants' health outcomes as the main cause of low birth weight is premature birth (Behrman & Rosenzweig, 2004; Eiríksdóttir et al., 2013; Pojda & Kelley, 2000; Strauss, 2000). Second, birth weight of infants could partly reflect changes in gestational age. We can normalize and deflate birth weight so that the estimates can compare how much of the effects on birth weight is through changes in gestational age rather than changes in per-week of gestation growth. Finally, this outcome is a common choice in the literature of pollution and birth outcomes (Behrman & Rosenzweig, 2004; Maisonet et al., 2004; Malmqvist et al., 2011, 2017; Nobles et al., 2019; Ritz et al., 2014).

Schifano et al., 2013; Strand et al., 2011b; Sun et al., 2019; Wang et al., 2020; Wang et al., 2020). These variables may co-move with precipitation as there reveal seasonality patterns of changes. To account for these variations, we include average county-level temperature and humidity in W and V in first and second stage regressions, respectively.

The matrix of fixed effects, represented by ζ and ξ in the first and second stage, include the child's gender, race, county-by-month fixed effects, and year-by-month fixed effects. The county-by-month fixed effects control for all seasonality in atmospheric variables and pollution that could alter the associations. They allow the variation to come from precipitation-induced changes in pollution within a county-month. The year-by-month fixed effects account for all nonlinearities in birth outcomes across months and years. The set of county fixed effects (included in county-month fixed effects) absorb all county-specific characteristics of local areas that do not vary by time. We cluster standard errors at the county level to control for serial autocorrelation in the error terms.

4. Results

4.1. Atmospheric Measures and Air Pollution

To explore the relevance assumption and first stage effects, we employ the same set of fixed effects as discussed above and regress air pollution measures on precipitation measures. The results are reported in Table 2**Error! Reference source not found.** for models that incorporate a stricter set of fixed effects and adjust for more covariates in consecutive columns. The estimated effects suggest a strong and negative association between precipitation and air pollution. The magnitudes of the marginal effects are statistically and economically meaningful. For instance, a one-standard-deviation increase in precipitation is associated with 6.5 and 12.2 percent of a standard-deviation decrease in ozone and PM10, respectively. Overall, these results point to strong first stage effects and are in line with several studies that suggest an association between pollution and precipitation (Aw and Kleeman, 2003; Breitner et al., 2014; Buckley et al., 2014; Liu et al., 2020; Roberts, 2004).

4.2. Ordinary Least Square Results

We start our analysis by exploring the OLS association between air pollution and birth outcomes. We employ regressions that include the same set of fixed effects and are adjusted by parental characteristics as we discussed in section 3.5. The results are reported in panels A and B of **Error! Reference source not found.** Table 3 for using ozone and PM10 as the explanatory variables, respectively. We observe some statistical association between air pollution and birth outcomes. The effects are, however, economically small. For instance, a one-standard-deviation rise in ozone and PM10 decreases birth weight by 1 and 1.6 grams. The marginal effects are small but statistically significant.

Figure 3 depicts the density distribution of birth weight in counties at the bottom quartile of Pm10 (ozone) distribution versus counties at the top-three quartiles in the top (bottom) panels. As one can observe, there is a slight shift in birth weight distribution to the right for counties at the bottom quartile of pollution distribution. However, these are visual correlations and offer only spurious links. Generally, the relationship between local pollution and birth outcomes could reveal a spurious correlation. For instance, pollution is higher in industrialized and urbanized places where there are also more job opportunities and better access to hospitals and healthcare. These factors are shown to positively affect birth outcomes (Hoynes et al., 2015; Lindo, 2011). Therefore, the OLS regressions underestimate the true effects of air pollution on infants' health. On the other hand, there is evidence of social inequality in exposure to pollution. Households with lower socioeconomic status and lower education are more likely to reside in places with higher levels of pollution (Christensen et al., 2020; Goodman et al., 2011; Hajat et al., 2015). A likely channel is that more polluted areas have, on average, lower home values (Hanna, 2007). Since children of lower socioeconomic status families are more likely to reveal adverse birth outcomes, the OLS regressions overestimate the true effects. We add to the literature by using a novel instrument based on atmospheric data: precipitation. These results are reported in the following subsection.

4.3. Two-Stage-Least-Square Instrumental-Variable Results

The results of two-stage least-square estimations introduced in equations 1 and 2 are reported in panels A and B of Table 4**Error! Reference source not found.** for ozone and PM10, respectively.[9] We report the coefficient, standard error, R-squared, mean of the dependent variable, and the implied percentage change (coefficient divided by the mean of the outcome) in subsequent rows within each panel. The F-statistics (reported in the last row of each panel) are above conventional limits for weak instruments and rule out concerns of weak instrumental-variable estimates.

We observe considerable reductions in birth weight and increases in low birth weight and very low birth weight. For instance, a one-standard-deviation rise in ozone and PM10 is associated with 20.1 and 19.5 grams lower birth weight, respectively (column 1). The same increase in ozone and PM10 is associated with a 6.4 and 5.9 percent rise (from the mean) in the share of low birth weight infants, and a 9.5 and 10.7 percent rise in the share of infants with very low birth weight (columns 2-3). This comparison suggests that the adverse effects of air pollution are more pronounced for infants at the lower tail of birth weight distribution.

[9] In Appendix G, we also examine the impacts of $PM_{2.5}$ as the endogenous pollutant regressor and find effects that are considerably larger than those of PM_{10}.

The effects on full-term birth weight suggest smaller effects compared with birth weight (column 4). The effects on fetal growth suggest a significant reduction of 0.27-0.39 grams/week for a one-standard-deviation rise in air pollution measures (column 5). The effects on gestational weeks are larger than the OLS estimates of Table 3 and statistically significant (column 6). Besides, we observe significant increases in very preterm birth (column 7). A one-standard-deviation rise in ozone and PM10 is associated with 12.8 and 21.5 percent rises in the share of very premature births, respectively.

These findings are considerably larger than the OLS estimates of Table 3 which suggests the endogeneity issues underestimate the relationships between air pollution and birth outcomes. Moreover, these findings are in line with several other studies. For instance, Currie et al. (2009) employ data from New Jersey and include family fixed effects and find that a one-standard-deviation rise in ozone and PM10 during the last trimester is associated with 4.9 and 1.2 grams lower birth weight (compare with 19-20 grams in our results). Palma et al. (2022) use variation in rainfall shocks as an instrument for exogenous variation in air pollution and find that a one-standard-deviation rise in PM10 is associated with a 22 percent reduction in the prevalence of low birth weight (compare with 6 percent in panel B, column 2, Table 4).

To gain an intuition of the magnitude of our findings, we can compare the implied effects with other shocks using studies that employ similar data over a similar period. For instance, Noghanibehambari and Salari (2020) use the NCHS birth record data over the years 1990-2017 and show that welfare payments under the Unemployment Insurance program improve birth outcomes. Their estimates suggest that a \$1,000 increase in benefits is associated with roughly 13.5 grams higher birth weight among likely affected women. Therefore, a \$1,000 increase in welfare spending can roughly be offset by a 0.7 standard-deviation rise in ozone or PM10. Hoynes et al. (2015) explore the externality of tax rebates under Earned Income Tax Credit (EITC) programs on infants' health outcomes. They employ NCHS birth data over the years 1983-1999 and find that a \$1,000 treatment-on-treated effect is associated with roughly 2.2-2.9 percent reduction in low birth weight. Therefore, a one-standard-deviation reduction in ozone or PM10 is equivalent to about a \$2,000-\$2,700 rise in the EITC welfare payments.

4.4. Endogeneity Concerns

There are four concerns that threaten the validity of our instrument which we discuss below. First, there is seasonality in precipitation that could be also observed in birth outcomes (Strand et al., 2011). To control for all unobserved factors related to seasonality in birth, instruments, and pollution measures, we allow for fixed effects of the county to vary by month of birth. We also interact birth-month fixed effects with birth-year fixed effects in our model. Therefore, we use the variation of within county-month and within month-year-of-birth. Although we are aware that the inclusion of fixed effects does not completely absorb seasonality in the effects, we expect that a large portion of confounding effects of seasonality is captured by this comprehensive set of fixed effects.

Second, another concern is the potential association between compositional change in birth outcome and our instruments. For instance, if parents systematically chose to give birth in specific months of the year and this decision varies by their characteristics, then our instruments pick up on those characteristics rather than providing exogenous variations. We explore this source by implementing a series of balancing tests where the outcome is parental characteristics and the explanatory variables are standardized values of precipitation. These regressions are conditional on county-by-month and year-by-month fixed effects. The results are reported in Table 5. There is no significant association between precipitation and mother age, race, education, smoker status, having any prenatal visits, father age, and father race. The marginal effects are statistically insignificant and economically quite small. For instance, a one-standard-deviation change in precipitation is correlated with a 0.06 percent change (from the mean) of the share of nonwhite mothers. Overall, these findings do not provide convincing evidence that selective fertility could hinder the exclusion restriction assumption. However, we should note that the range of parental outcomes studied in Table 5 is limited and is restricted to sociodemographic features. Parents may choose birth timing and also exercise pollution avoidance based on their cultural opinions and religious values. Unfortunately, our data does not provide any information regarding these variables. Therefore, there is remaining uncertainty about the influence of these characteristics in delivery timing.

Third, it is also possible to assume that county demographic composition and socioeconomic characteristics respond to changes in precipitation. For instance, a steady reductions in precipitation may hamper the agricultural sector and force out-migration of specific subpopulations (Beine and Jeusette, 2021). Since sociodemographic characteristics could, in many ways, influence birth outcomes, such demographic shifts could threaten the validity of our instruments. To explore this concern, we regress a series of county-level characteristics on precipitation conditioning on county-month and year-month fixed effects. The results are reported in Table 6. We do not observe consistent and strong evidence of this source of endogeneity. For instance, a one-standard-deviation change in precipitation is correlated with 0.2 percent change in the share of blacks, 34 dollars lower per capita income (off a mean of $18K), 0.6 dollar lower weekly wage (off a mean of $428), and 0.3 percent lower share of manufacturing. These effects are quite small in magnitude and in almost all cases statistically insignificant at 10 percent level.

Fourth, to satisfy the exclusion restriction assumption, the instrument requires to operate only through the endogenous variable and do not have a direct impact on the outcome. To validate this, we regress birth outcomes on precipitation while controlling for pollution, humidity, temperature, and a full set of fixed effects. The results, reported and discussed in Appendix I, fail to provide a direct link between precipitation and birth outcomes.

4.5. Placebo Tests

To better validate the results of Table 4**Error! Reference source not found.** and provide evidence that the exposure during in-utero rather than other periods drives the main results, we implement a series of placebo tests in which we assign air pollution measures for the time infants are two years old. We expect that postnatal exposure to pollution should not reveal any negative effects on birth outcomes. We replicate the two-stage-least-square instrumental-variable estimates and report the results in Table 7. There is no significant association between postnatal air pollution and birth outcomes. All the marginal effects are quite small in magnitude and statistically insignificant.

4.6. Robustness Checks

In Table 8, we explore the robustness of the main results to alternative specifications. In panel A, we allow for county fixed effects to vary by gender and race of the child. We assume that the time-invariant features of the county could have unobserved effects on birth outcomes that differ by gender and race. The interaction of county-gender and county-race fixed effects accounts for these unobserved factors. We observe similar coefficients for both ozone and PM10 and for all outcomes. These effects are quite comparable with our findings of Table 4**Error! Reference source not found.**.

In the main analyses, we avoid including any county-level controls as these controls are highly collinear with air pollution and absorb much of the variations in our identification. However, in panel B of Table 8, we include a series of county and state-level controls. County controls include per capita income, per capita unemployment insurance payments, per capita dividend income, average weekly wage, percentage of employment in manufacturing, percentage of employment in construction industries, percentage of whites, percentage of blacks, percentage of males, and percentage of people aged 25-65. State-level controls include per capita gross state product, unemployment rate, union coverage rate, Medicaid coverage rate, welfare reform, per capita income maintenance benefit, per capita current transfer receipts, and minimum wage. We observe slight reductions in the marginal effects. For instance, the effects of ozone and PM10 on low birth weight drop from 0.0041-0.0037 in the main results to around 0.0023-0.0034 in panels B1 and B2 of Table 8.

In Appendix C, we explore the effects of lagged values of air pollution, i.e., the assignment of pollution in pre-prenatal development period. We find small and mostly insignificant effects suggesting that the effects are primarily concentrated for the in-utero period.

Furthermore, in Appendix D, we show the robustness of the results to the functional form and explore the nonlinearities in the effects by replacing the pollution exposures and instruments with the logarithm of their respective values. We discuss that the magnitude of the effects are comparable to those of the main results.

As an additional robustness check, we add controls for local and seasonal variations in incidences of wildfire into our regressions. We report and discuss the findings in Appendix H. We find that the results are comparable to the main findings.

4.7. Heterogeneity across Trimesters

Studies show that the effects of air pollution on birth outcomes could be heterogeneous across trimesters of pregnancy and suggest that they are more pronounced during second and third trimesters (Currie et al., 2009; Lavigne et al., 2016; Lee et al., 2013; Ross et al., 2013). We explore this source of heterogeneity by assigning pollution at different trimesters and evaluate the effects of pollution on the birth outcomes for each trimester using the same two-stage-least-square instrumental-variable approach as the main results. The estimated effects are reported in two panels of Table 9. The effects appear to be slightly larger in the second and third trimesters specifically for PM10 exposure. For instance, a one-standard-deviation rise in PM10 during the first, second, and third trimesters is associated with a 13.4, 16.8, and 18.7 grams reduction in birth weight, respectively (panel B, column 1). We observe a similar pattern for other outcomes. A one-standard-deviation change in ozone during first, second, and third is associated with 0.39, 0.46, and 0.41 grams/week reductions in fetal growth, respectively. Therefore, the evidence points to the relevance of later months of pregnancy for the adverse impacts of air pollution on infants' health outcomes. However, we should note that infants' health outcomes studied here refer to their physical growth outcomes and excludes other measures of health outcomes such as mental health, congenital malformation, fetal deaths, abortions, recognized syndromes, and various anomalies and abnormalities.

5. Discussion and Conclusion

Quantifying the adverse effects of air pollution on health outcomes is important for policymakers both in areas of health and environment. It adds to the costs associated with pollution and helps policymakers in evaluating more refined pollution abatements. Evaluating the costs associated with pollution is important as the levels of pollution have steadily risen during the past decades and studies reveal no declining pattern (Liu et al., 2019). The current paper aimed to do so by quantifying the impact of air pollution on birth outcomes.

Our identification strategy design exploits within county-month variations in air pollution measures that are caused by changes in precipitation. Our findings suggest significant adverse impacts on birth outcomes. The effects are more pronounced for infants at the lower tail of birth weight and gestational age distribution. Going from the least polluted county in our sample (Hancock, Main) to the most polluted county (Pinal, Arizona), the pollution measure of PM10 increases from 5.2 $\frac{\mu g}{m^3}$ to 50.5 $\frac{\mu g}{m^3}$, an increase of 5.9 standard deviation of PM10 over the sample period. The results suggest that this increase in pollution is associated with 118 grams lower birth weight and a 37 percent higher share of low birth weight infants. A series of placebo tests show that the effects are specific to exposure during prenatal development. Finally, we also show that these effects are heterogeneous across trimesters with the largest effects in the second and third trimesters. This study concludes that air pollution have a negative and statistically significant impact on the weight of infants. Thus, policy makers need apply various environmental policies to reduce air pollution at the county level in the U.S. to have healthy generation.

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Tables

Table 1 - Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Average Infants' Characteristics:				
Birth Weight (in grams)	3292.851	318.895	227	7777
Low Birth Weight	.07	.136	0	1
Very Low Birth Weight	.012	.058	0	1
Full-Term Birth Weight (grams)	3376.137	271.733	804	7777
Fetal Growth (grams/week)	84.829	7.395	9.08	210.189
Gestational Age (weeks)	38.792	1.381	17	47
Very Premature Birth	.007	.043	0	1
Birth Counts	45.952	152.467	1.007	8120.813
Average Parental Characteristics:				
Age of Mother	26.127	3.348	11	51
Mother Race: Black	.238	.398	0	1
Mother Hispanic	.027	.096	0	1
Mother Race: Other	.104	.272	0	1
Father Race: White	.574	.402	0	1
Father Race: Black	.132	.253	0	1
Father Hispanic	.023	.083	0	1
Mother's Education Missing	.048	.199	0	1
Mother's Education< High School	.024	.085	0	1
Mother's Education=High School	.502	.296	0	1
Mother's Education Some College	.242	.232	0	1
Mother's Education Bachelor	.116	.169	0	1
Mother's Education Master-PHD	.068	.129	0	1
Mother Cigar/Tobacco Smoker	.143	.204	0	1
Any Prenatal Visits	.964	.106	0	1
Father's Age<30	.207	.214	0	1
Exposure Measures:				
PM10 ($\frac{\mu g}{m^3}$)	22.931	7.995	-100.547	174.626
Standardized PM10	0	1	-15.444	18.973
Ozone ($\frac{\mu g}{m^3}$)	28.55	6.996	-116.617	137.543
Standardized Ozone	0	1	-20.75	15.579
Precipitation (inch)	6.445	6.226	-148.467	468.571
Standardized Precipitation	0	1	-24.88	74.221
Observations		535,036		
No. of Pre-Collapse Observations		69,936,360		

Table 2 - First Stage Effects of Instruments on Pollution Outcomes

	Outcomes:					
	Ozone (STD)			PM10 (STD)		
	(1)	(2)	(3)	(4)	(5)	(6)
Precipitation (STD)	-.06188***	-.06034***	-.06505***	-.12671***	-.12511***	-.12176***
	(.01668)	(.01657)	(.0167)	(.02969)	(.03062)	(.02726)
Observations	535036	535036	535036	392419	392417	392417
R-squared	.66233	.69027	.69406	.78829	.79629	.8035
County Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
County-by-Month Fixed Effects	No	Yes	Yes	No	Yes	Yes
County Controls	No	No	Yes	No	No	Yes

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions are weighted using the total number of births in each county.
*** p<0.01, ** p<0.05, * p<0.1

Table 3 - The results of OLS Regressions of Pollution on Birth Outcomes

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A.			
Ozone (STD)	-1.07985**	.00019	.00006	-.64488*	-.02318**	-.00222	.00002
	(.47762)	(.00012)	(.00004)	(.38525)	(.00941)	(.00257)	(.00003)
Observations	798022	798022	798022	792308	798022	798022	798022
R-squared	.71949	.34556	.14608	.73643	.71574	.43423	.11265
Mean DV	3311.207	0.064	0.012	3390.830	85.283	38.819	0.006
%Change	-0.033	0.292	0.504	-0.019	-0.027	-0.006	0.346
				Panel B.			
PM10 (STD)	-1.60888*	.0008***	.00013**	-.48865	-.01324	-.0134***	.00013***
	(.88414)	(.00021)	(.00006)	(.76308)	(.01771)	(.00502)	(.00005)
Observations	545989	545989	545989	541805	545989	545989	545989
R-squared	.74984	.39671	.1813	.75999	.74275	.48556	.14522
Mean DV	3312.907	0.064	0.012	3392.476	85.271	38.845	0.006
%Change	-0.049	1.245	1.043	-0.014	-0.016	-0.034	2.221

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.

*** p<0.01, ** p<0.05, * p<0.1

Table 4 - The Results of Two-Stage-Least-Square Instrumental-Variable Regressions of Pollution on Birth Outcomes

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
Ozone (STD)	-20.09637***	.00409**	.00114**	-14.57308***	-.39178***	-.06353*	.00077*
	(6.31102)	(.00163)	(.00046)	(5.5523)	(.11123)	(.03577)	(.00041)
Observations	535036	535036	535036	532693	535036	535036	535036
R-squared	.08273	.05176	.0263	.05317	.06441	.04515	.02205
Mean DV	3309.772	0.064	0.012	3389.140	85.260	38.814	0.006
%Change	-0.607	6.383	9.527	-0.430	-0.460	-0.164	12.819
F-Stat	63.970	75.439	162.420	56.815	66.054	74.664	136.850
			Panel B.				
PM10 (STD)	-19.49962***	.00378**	.00129***	-12.59806**	-.2778**	-.10734***	.00129***
	(6.32009)	(.00159)	(.00046)	(5.74615)	(.11034)	(.03613)	(.00045)
Observations	392417	392417	392417	390266	392417	392417	392417
R-squared	.10884	.06797	.0328	.07145	.08856	.04286	.02577
Mean DV	3312.433	0.064	0.012	3391.491	85.278	38.837	0.006
%Change	-0.589	5.911	10.721	-0.371	-0.326	-0.276	21.568
F-Stat	64.941	65.865	158.921	52.106	60.370	64.321	124.001

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.

*** p<0.01, ** p<0.05, * p<0.1

Table 5 - Exploring for Endogenous Fertility

	Outcomes:											
	Mother Age	Is Mother Nonwhite	Mother Education Missing	Mother's Education< High School	Mother's Education= High School	Mother's Education Some College	Mother's Education Bachelor	Mother's Education Master-PHD	Is Mother Smoker	Any Prenatal Visits	Is Father Nonwhite	Father Age<30
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Precipitation (STD)	-.02981	.00017	.00513	-.00061	-.00227	-.00099	-.00224	.00098	-.0043	.00155	.00049	-.00075
	(.02216)	(.00149)	(.00686)	(.001)	(.00305)	(.00252)	(.0019)	(.00131)	(.00321)	(.00252)	(.00168)	(.00108)
Observations	665833	665833	665833	665833	665833	665833	665833	665833	665833	665833	665833	665833
R-squared	.68095	.96202	.29683	.49758	.56369	.30447	.44968	.44444	.52638	.27642	.92452	.49915
Mean DV	27.625	0.284	0.050	0.034	0.416	0.230	0.167	0.103	0.074	0.949	0.412	0.163

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include county-by-month fixed effects and year-by-month fixed effects. The regressions are weighted using the total number of births in each cell.
*** p<0.01, ** p<0.05, * p<0.1

Table 6 - Exploring for Endogeneity of Instruments with Respect to County Demographic and Socioeconomic Characteristics

	Outcomes:							
	%Blacks	%Whites	%Males	%Individuals 25-55	Real Per Capita Income (in 1980 dollars)	Average Weekly Wage	Real Per Capita Rent-Dividend Income	Share of Manufacturin g Employment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Precipitation (STD)	.03344	-.03957	-.00595	.02155	-34.63578	.59121	-4.53999	-.00818
	(.02402)	(.02476)	(.00396)	(.01397)	(23.81485)	(.41258)	(8.56365)	(.00582)
Observations	1337387	1337387	1337387	1337387	1319189	1337387	1319189	1312821
R-squared	.9992	.99921	.98365	.98908	.986	.95695	.98091	.98643
Mean DV	13.903	79.338	49.081	52.352	1.8e+04	387.699	3564.765	2.989

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include county-by-month fixed effects and year-by-month fixed effects. The regressions are weighted using the total number of births in each cell.

*** p<0.01, ** p<0.05, * p<0.1

Table 7 - Placebo Tests: Assigning Pollution at Age 2

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A.			
Ozone (STD)	-1.25462	.00022	.00023	-0.932729	-.04196	-.02836	.00035
	(1.48365)	(.00055)	(.0003)	(0.9967)	(.06073)	(.01945)	(.00026)
Observations	523312	523312	523312	521017	523312	523312	523312
R-squared	.10732	.05809	.02855	.07427	.08443	.05366	.02387
Mean DV	3311.889	0.064	0.012	3391.180	85.283	38.828	0.006
F-Stat	62.715	81.340	162.808	56.585	65.619	66.604	125.570
				Panel B.			
PM10 (STD)	-2.39068	.00082	.00022	-1.68589	-.05254	-.01949	.00021
	(2.01762)	(.00049)	(.00016)	(1.74147)	(.03566)	(.01073)	(.00014)
Observations	370976	370976	370976	368936	370976	370976	370976
R-squared	.13787	.07482	.03612	.09436	.10602	.06881	.03077
Mean DV	3314.655	0.064	0.012	3393.556	85.295	38.855	0.006
F-Stat	62.312	81.521	141.114	52.328	59.324	59.108	113.159

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.

*** p<0.01, ** p<0.05, * p<0.1

Table 8 - Robustness of the Main Results to Alternative Specifications

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. Adding County-by-Gender and County-by-Race Fixed Effects						
	Panel A1.						
Ozone (STD)	-18.6035***	.00354**	.00102**	-13.33241**	-.35454***	-.06206*	.00069*
	(6.38252)	(.0016)	(.00047)	(5.87393)	(.11498)	(.03543)	(.00041)
Observations	535035	535035	535035	532692	535035	535035	535035
R-squared	.00975	.00629	.00264	.00985	.0111	.00539	.0026
Mean DV	3309.772	0.064	0.012	3389.140	85.260	38.814	0.006
	Panel A2.						
PM10 (STD)	-17.66081***	.00358**	.00133***	-10.47613*	-.23294**	-.10572***	.00129***
	(6.27612)	(.00157)	(.00048)	(6.22715)	(.11388)	(.03568)	(.00045)
Observations	392415	392415	392415	390264	392415	392415	392415
R-squared	.01542	.00804	.00112	.01702	.01963	-.0074	-.0006
Mean DV	3312.433	0.064	0.012	3391.491	85.278	38.837	0.006
	Panel B. Adding County/State Controls						
	Panel B1.						
Ozone (STD)	-17.96992***	.0032**	.0011***	-12.96867**	-.37069***	-.04692	.00074**
	(5.71289)	(.00131)	(.0004)	(5.19932)	(.10282)	(.03046)	(.00035)
Observations	525138	525138	525138	522877	525138	525138	525138
R-squared	.08754	.0533	.02638	.05741	.06736	.04966	.02225
Mean DV	3309.712	0.064	0.012	3389.061	85.261	38.812	0.006
	Panel B2.						
PM10 (STD)	-20.07057***	.00338**	.00137***	-13.01564**	-.31389***	-.09694***	.00126***
	(6.72598)	(.00161)	(.00048)	(6.44764)	(.12017)	(.03733)	(.00042)
Observations	380439	380439	380439	378392	380439	380439	380439
R-squared	.11208	.06908	.03277	.07438	.09015	.05027	.02652
Mean DV	3312.382	0.064	0.012	3391.363	85.277	38.836	0.006

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell. County controls include per capita income, per capita unemployment insurance payments, per capita dividend income, average weekly wage, percentage employment in manufacturing, percentage employment in construction industries, percentage of whites, percentage of blacks, percentage of males, and percentage of people aged 25-65. State-level controls include per capita gross state product, unemployment rate, union coverage rate, Medicaid coverage rate, welfare reform, per capita income maintenance benefit, per capita current transfer receipts, and minimum wage.

*** p<0.01, ** p<0.05, * p<0.1

Table 9 - Heterogeneity of the Effects across Trimesters

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. IDV: Ozone (STD) across Trimesters						
First Trimester	-21.67556***	.00452***	.00136***	-15.66759***	-.39834***	-.07813**	.0011***
	(5.83785)	(.00151)	(.00042)	(5.16372)	(.09871)	(.03406)	(.00039)
Observations	527079	527079	527079	524792	527079	527079	527079
R-squared	.08429	.05198	.02622	.05445	.06696	.04351	.02133
Second Trimester	-24.22917***	.00485***	.00151***	-17.46817***	-.45567***	-.08329**	.00115***
	(6.88614)	(.00178)	(.00047)	(6.01997)	(.11693)	(.03997)	(.00044)
Observations	530369	530369	530369	528045	530369	530369	530369
R-squared	.0779	.05079	.02549	.04984	.06188	.04078	.02084
Third Trimester	-21.11832***	.00423**	.00118***	-15.33635***	-.40621***	-.06815*	.00088**
	(6.42056)	(.00165)	(.00044)	(5.6797)	(.11237)	(.03678)	(.0004)
Observations	533510	533510	533510	531301	533510	533510	533510
R-squared	.08231	.05182	.02761	.0521	.06452	.04496	.02453
	Panel B. IDV: PM10 (STD) across Trimesters						
First Trimester	-13.41283***	.00267***	.00093***	-9.15798***	-.20663***	-.06672***	.0008***
	(3.67413)	(.00091)	(.00029)	(3.31144)	(.06261)	(.02107)	(.00028)
Observations	377837	377837	377837	375759	377837	377837	377837
R-squared	.11821	.06981	.03403	.07696	.0926	.05606	.0283
Second Trimester	-16.86215***	.00316**	.00119***	-11.21681**	-.24704***	-.08981***	.00108***
	(5.21495)	(.00131)	(.00038)	(4.67153)	(.08947)	(.02952)	(.00037)
Observations	383790	383790	383790	381665	383790	383790	383790
R-squared	.11368	.06903	.03332	.07405	.09065	.04961	.02715
Third Trimester	-18.75114***	.00351**	.00127***	-12.17497**	-.27032**	-.10164***	.00124***
	(6.09378)	(.00154)	(.00044)	(5.54282)	(.10607)	(.03473)	(.00043)
Observations	389640	389640	389640	387599	389640	389640	389640
R-squared	.11203	.06914	.03518	.0723	.0905	.04647	.03021

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.
*** p<0.01, ** p<0.05, * p<0.1

Figures

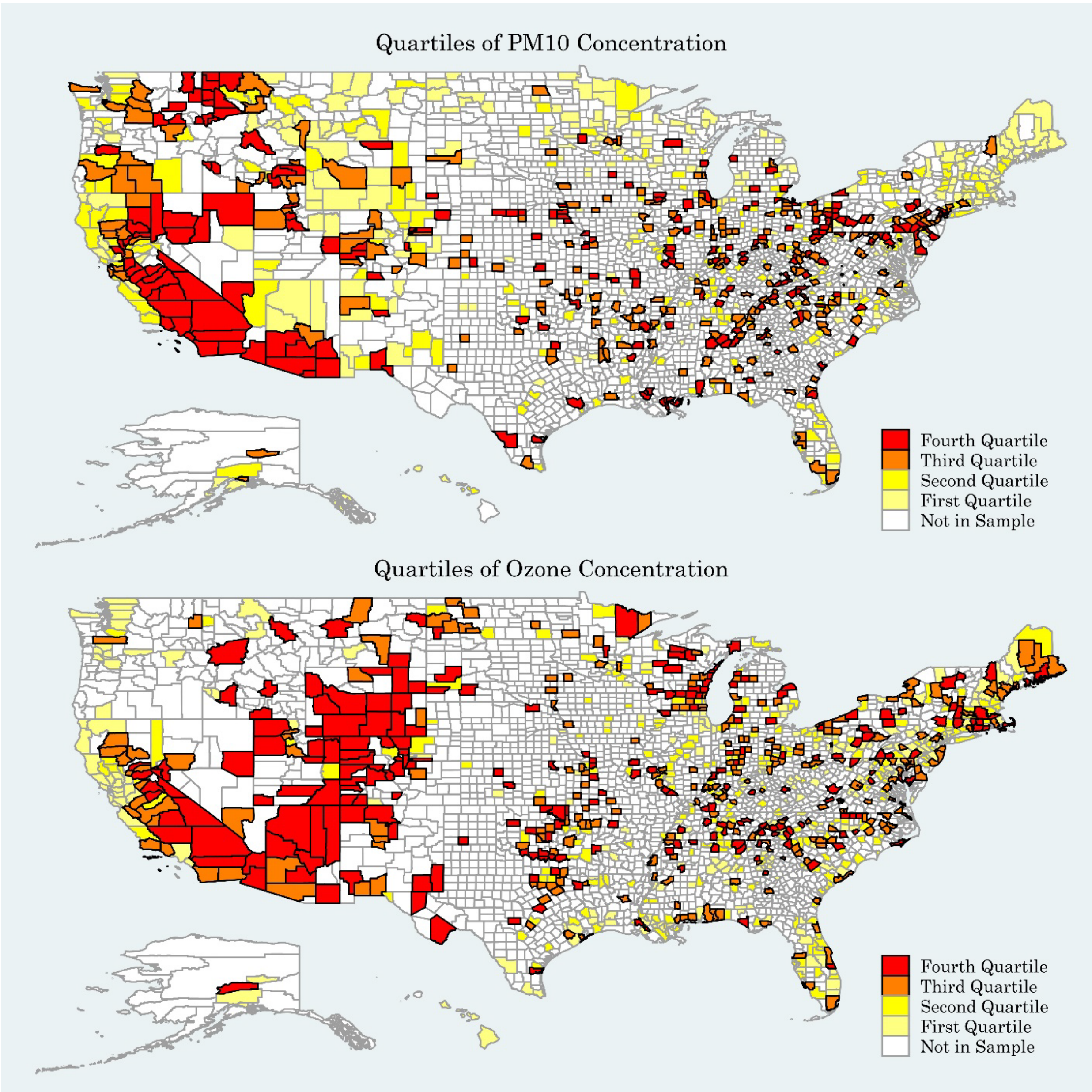

Figure 1 - Geographic Distribution of Pollution Measures across US Counties

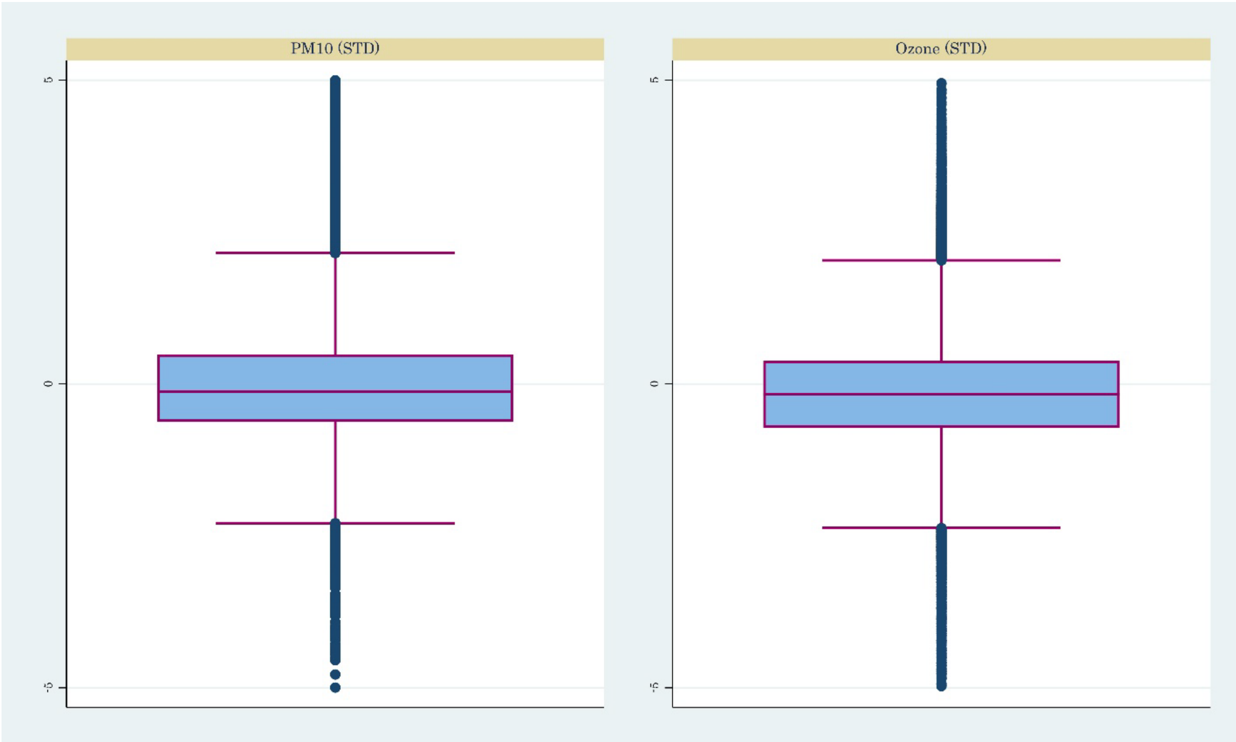

Figure 2 - Boxplots of Instruments and Endogenous Variables

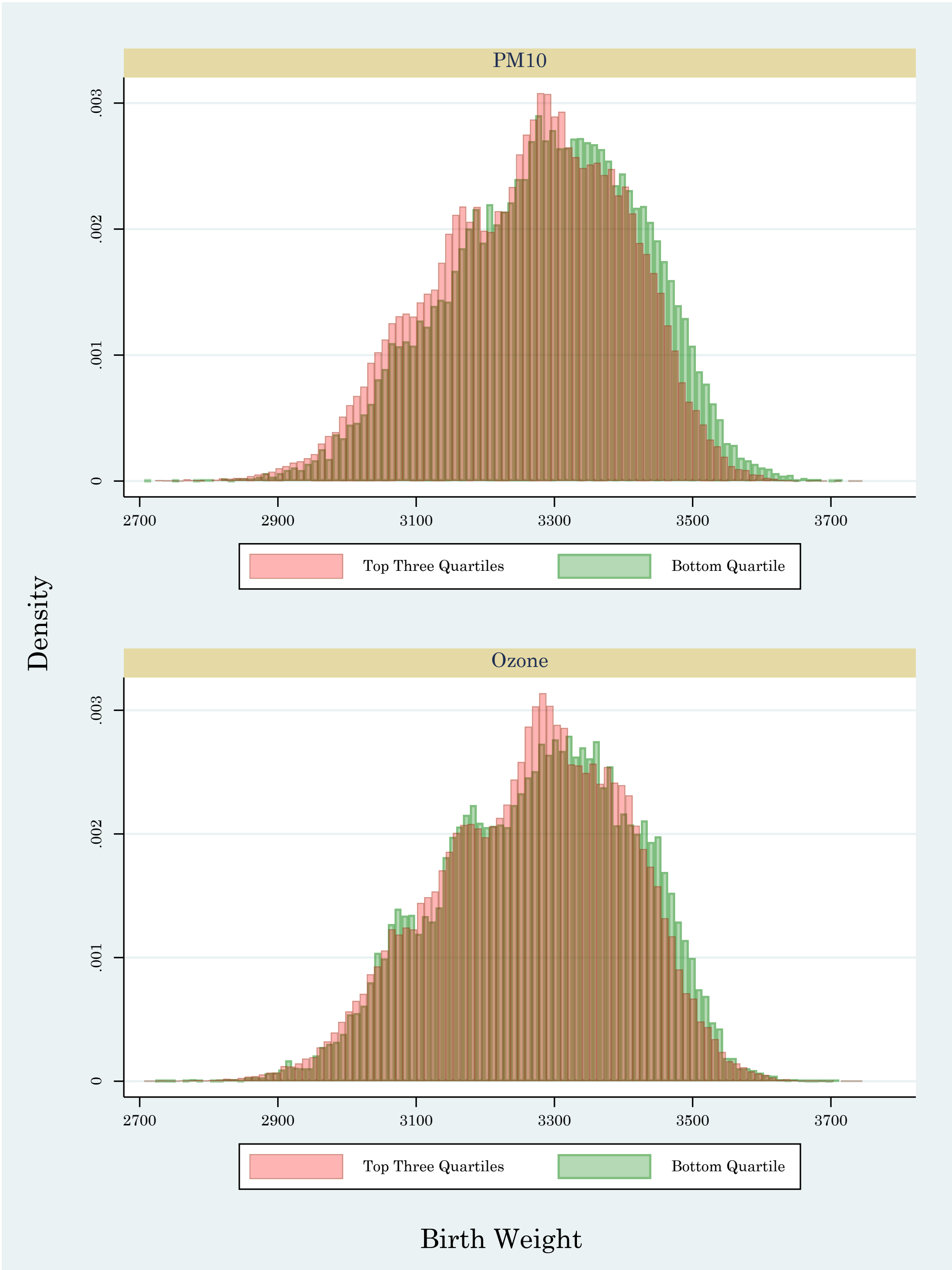

Figure 3 - Density Distribution of Birth Weight in High/Low Oil-Gas Production Counties

Appendix A

In Appendix Table A-1 through Appendix Table A-4, we list the counties that are used in the final sample. We should note that not all counties have pollution data for all years. The counties in this table are those that were used for at least a year in the final sample. However, for the years that they do have pollution data, the data is available in all months.

Appendix Table A-1 - List of Counties in the Final Sample

Abbeville, South Carolina	Barnwell, South Carolina	Burleigh, North Dakota	Chemung, New York	Contra Costa, California
Ada, Idaho	Bartholomew, Indiana	Burlington, New Jersey	Cherokee, Georgia	Converse, Wyoming
Adair, Oklahoma	Bay, Florida	Butler, Ohio	Cherokee, Oklahoma	Cook, Illinois
Adams, Colorado	Beaufort, South Carolina	Butte, California	Cherokee, South Carolina	Coos, New Hampshire
Adams, Illinois	Beauregard, Louisiana	Butte, Idaho	Cheshire, New Hampshire	Cotton, Oklahoma
Adams, Mississippi	Beaver, Pennsylvania	Cabell, West Virginia	Chester, Pennsylvania	Coweta, Georgia
Adams, Pennsylvania	Becker, Minnesota	Cache, Utah	Chester, South Carolina	Cowlitz, Washington
Aiken, South Carolina	Belknap, New Hampshire	Caddo, Louisiana	Chesterfield, S Carolina	Creek, Oklahoma
Alachua, Florida	Bell, Kentucky	Caddo, Oklahoma	Chesterfield, Virginia	Crittenden, Arkansas
Alameda, California	Bell, Texas	Calaveras, California	Chippewa, Michigan	Crow Wing, Minnesota
Alamosa, Colorado	Bennington, Vermont	Calcasieu, Louisiana	Chippewa, Wisconsin	Culberson, Texas
Albany, New York	Benzie, Michigan	Caldwell, North Carolina	Chittenden, Vermont	Cumberland, Maine
Albany, Wyoming	Bergen, New Jersey	Callaway, Missouri	Choctaw, Mississippi	Cumberland, New Jersey
Albemarle, Virginia	Berkeley, South Carolina	Calvert, Maryland	Choctaw, Oklahoma	Cumberland, N Carolina
Alcorn, Mississippi	Berkeley, West Virginia	Cambria, Pennsylvania	Christian, Kentucky	Custer, South Dakota
Alexander, North Carolina	Berks, Pennsylvania	Camden, New Jersey	Churchill, Nevada	Cuyahoga, Ohio
Alexandria city, Virginia	Berkshire, Massachusetts	Camden, North Carolina	Clackamas, Oregon	Daggett, Utah
Allegan, Michigan	Bernalillo, New Mexico	Cameron, Texas	Claiborne, Tennessee	Dakota, Minnesota
Allegany, Maryland	Berrien, Michigan	Campbell, Kentucky	Clallam, Washington	Dallas, Texas
Allegheny, Pennsylvania	Bexar, Texas	Campbell, Wyoming	Clark, Arkansas	Dane, Wisconsin
Allen, Indiana	Bibb, Georgia	Canadian, Oklahoma	Clark, Illinois	Darlington, South Carolina
Allen, Ohio	Big Horn, Wyoming	Canyon, Idaho	Clark, Indiana	Dauphin, Pennsylvania
Amador, California	Billings, North Dakota	Carbon, Utah	Clark, Nevada	Davidson, Tennessee
Amherst, Virginia	Blair, Pennsylvania	Carbon, Wyoming	Clark, Ohio	Davie, North Carolina
Anchorage; Alaska	Blount, Tennessee	Carlton, Minnesota	Clark, Washington	Daviess, Kentucky
Anderson, South Carolina	Bolivar, Mississippi	Caroline, Virginia	Clarke, Georgia	Davis, Utah
Anderson, Tennessee	Boone, Indiana	Carroll, Indiana	Clay, Alabama	Dawson, Georgia
Andrew, Missouri	Boone, Kentucky	Carroll, Maryland	Clay, Missouri	De Kalb, Alabama
Androscoggin, Maine	Boone, Missouri	Carroll, New Hampshire	Clear Creek, Colorado	De Kalb, Georgia
Anne Arundel, Maryland	Bossier, Louisiana	Carson City, Nevada	Clearfield, Pennsylvania	De Kalb, Indiana
Anoka, Minnesota	Boulder, Colorado	Carter, Kentucky	Clermont, Ohio	De Kalb, Tennessee
Apache, Arizona	Box Elder, Utah	Carter, Oklahoma	Cleveland, Oklahoma	De Soto, Mississippi
Arapahoe, Colorado	Boyd, Kentucky	Carteret, North Carolina	Clinton, Iowa	Del Norte, California
Archuleta, Colorado	Bradford, Pennsylvania	Cass, Michigan	Clinton, Michigan	Delaware, Indiana
Arlington, Virginia	Bradley, Tennessee	Cass, Missouri	Clinton, Missouri	Delaware, Ohio
Armstrong, Pennsylvania	Brazoria, Texas	Cass, North Dakota	Clinton, Ohio	Delaware, Pennsylvania
Aroostook, Maine	Bremer, Iowa	Cassia, Idaho	Cobb, Georgia	Denton, Texas
Ascension, Louisiana	Brevard, Florida	Caswell, North Carolina	Cochise, Arizona	Denver; Colorado
Ashland, Wisconsin	Brewster, Texas	Cecil, Maryland	Coconino, Arizona	Dewey, Oklahoma
Ashtabula, Ohio	Bristol, Massachusetts	Cedar, Missouri	Coffee, Tennessee	Dickinson, Michigan
Athens, Ohio	Brookings, South Dakota	Centre, Pennsylvania	Colbert, Alabama	Dickson, Tennessee
Atlantic, New Jersey	Broward, Florida	Chaffee, Colorado	Colleton, South Carolina	Dodge, Wisconsin
Augusta, Virginia	Brown, Indiana	Champaign, Illinois	Collier, Florida	Dona Ana, New Mexico
Autauga, Alabama	Brown, Wisconsin	Charles City, Virginia	Collin, Texas	Door, Wisconsin
Avery, North Carolina	Bryan, Oklahoma	Charles, Maryland	Columbia, Florida	Dorchester, Maryland
Baker, Florida	Bucks, Pennsylvania	Charleston, South Carolina	Columbia, Georgia	Douglas, Colorado
Baldwin, Alabama	Bullitt, Kentucky	Chatham, Georgia	Columbia, Oregon	Douglas, Georgia
Baltimore city, Maryland	Buncombe, North Carolina	Chatham, North Carolina	Columbia, Wisconsin	Douglas, Kansas
Baltimore, Maryland	Burke, North Carolina	Chattooga, Georgia	Colusa, California	Douglas, Nebraska
Barnstable, Massachusetts	Burke, North Dakota	Chautauqua, New York	Comanche, Oklahoma	Douglas, Nevada

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Appendix Table A-2 - List of Counties in the Final Sample

Du Page, Illinois	Fort Bend, Texas	Hamblen, Tennessee	Huron, Michigan	Kern, California
Duchesne, Utah	Franklin, Massachusetts	Hamilton, Illinois	Huron, Ohio	Kewaunee, Wisconsin
Dukes, Massachusetts	Franklin, Mississippi	Hamilton, Indiana	Iberville, Louisiana	King, Washington
Dunn, North Dakota	Franklin, New York	Hamilton, New York	Idaho, Idaho	Kings, California
Duplin, North Carolina	Franklin, North Carolina	Hamilton, Ohio	Imperial, California	Kleberg, Texas
Durham, North Carolina	Franklin, Ohio	Hamilton, Tennessee	Indian River, Florida	Klickitat, Washington
Dutchess, New York	Franklin, Pennsylvania	Hampden, Massachusetts	Indiana, Pennsylvania	Knox, Indiana
Duval, Florida	Frederick, Maryland	Hampshire, Massachusetts	Ingham, Michigan	Knox, Maine
Dyer, Tennessee	Frederick, Virginia	Hampton city, Virginia	Inyo, California	Knox, Nebraska
Baton Rouge, Louisiana	Fremont, Wyoming	Hancock, Indiana	Jackson, Alabama	Knox, Ohio
Eau Claire, Wisconsin	Fresno, California	Hancock, Kentucky	Jackson, Colorado	Knox, Tennessee
Eddy, New Mexico	Fulton, Georgia	Hancock, Maine	Jackson, Indiana	Koochiching, Minnesota
Edgecombe, N Carolina	Galveston, Texas	Hancock, Mississippi	Jackson, Mississippi	Kootenai, Idaho
Edgefield, South Carolina	Garfield, Colorado	Hancock, West Virginia	Jackson, Missouri	La Crosse, Wisconsin
Edmonson, Kentucky	Garfield, Utah	Hanover, Virginia	Jackson, North Carolina	La Plata, Colorado
Effingham, Illinois	Garrett, Maryland	Hardin, Kentucky	Jackson, Oregon	La Porte, Indiana
El Dorado, California	Geauga, Ohio	Hardin, Texas	Jackson, South Dakota	Lackawanna, Pennsylvania
El Paso, Colorado	Genesee, Michigan	Harford, Maryland	Jasper, Missouri	Lafayette, Louisiana
El Paso, Texas	Geneva, Alabama	Harris, Texas	Jefferson, Alabama	Lafourche, Louisiana
Elk, Pennsylvania	Gibson, Indiana	Harrison, Iowa	Jefferson, Colorado	Lake, California
Elkhart, Indiana	Gila, Arizona	Harrison, Mississippi	Jefferson, Kentucky	Lake, Florida
Ellis, Texas	Giles, Tennessee	Harrison, Texas	Jefferson, Louisiana	Lake, Illinois
Elmore, Alabama	Giles, Virginia	Hartford, Connecticut	Jefferson, Missouri	Lake, Indiana
Elmore, Idaho	Gillespie, Texas	Hawaii, Hawaii	Jefferson, New York	Lake, Minnesota
Erie, New York	Gilmer, West Virginia	Hays, Texas	Jefferson, Ohio	Lake, Ohio
Erie, Pennsylvania	Glenn, California	Haywood, North Carolina	Jefferson, Oklahoma	Lamar, Mississippi
Escambia, Florida	Gloucester, New Jersey	Haywood, Tennessee	Jefferson, Tennessee	Lancaster, Nebraska
Essex, Massachusetts	Glynn, Georgia	Henderson, Kentucky	Jefferson, Texas	Lancaster, Pennsylvania
Essex, New Jersey	Goodhue, Minnesota	Hendricks, Indiana	Jefferson, Wisconsin	Laramie, Wyoming
Essex, New York	Goshen, Wyoming	Hennepin, Minnesota	Jersey, Illinois	Larimer, Colorado
Etowah, Alabama	Grafton, New Hampshire	Henrico, Virginia	Jessamine, Kentucky	Latimer, Oklahoma
Fairbanks North, Alaska	Graham, North Carolina	Henry, Georgia	Jo Daviess, Illinois	Lauderdale, Mississippi
Fairfax city, Virginia	Grand, Colorado	Henry, Virginia	Johnson, Indiana	Lawrence, Alabama
Fairfax, Virginia	Grand, Utah	Herkimer, New York	Johnson, Iowa	Lawrence, Indiana
Fairfield, Connecticut	Grant, Louisiana	Hidalgo, Texas	Johnson, Kansas	Lawrence, Kentucky
Fannin, Georgia	Grant, New Mexico	Highlands, Florida	Johnson, Texas	Lawrence, Ohio
Fauquier, Virginia	Granville, North Carolina	Hillsborough, Florida	Johnston, North Carolina	Lawrence, Pennsylvania
Fayette, Georgia	Graves, Kentucky	Hillsborough, New Hampshire	Johnston, Oklahoma	Lawrence, Tennessee
Fayette, Ohio	Green, Wisconsin	Hinds, Mississippi	Kalamazoo, Michigan	Lea, New Mexico
Fayette, Tennessee	Greenbrier, West Virginia	Holmes, Florida	Kanawha, West Virginia	Leavenworth, Kansas
Fayette, Kentucky	Greene, Indiana	Honolulu, Hawaii	Kane, Illinois	Lebanon, Pennsylvania
Fergus, Montana	Greene, Missouri	Hood, Texas	Kaufman, Texas	Lee, Florida
Flagler, Florida	Greene, Ohio	Horry, South Carolina	Kay, Oklahoma	Lee, Mississippi
Flathead, Montana	Greene, Pennsylvania	Houston, Alabama	Kennebec, Maine	Lee, North Carolina
Florence, Wisconsin	Greenup, Kentucky	Hudson, New Jersey	Kenosha, Wisconsin	Leelanau, Michigan
Floyd, Indiana	Greenville, South Carolina	Humboldt, California	Kent, Delaware	Lehigh, Pennsylvania
Fond du Lac, Wisconsin	Gregg, Texas	Humphreys, Tennessee	Kent, Maryland	Lenawee, Michigan
Ford, Kansas	Guilford, North Carolina	Hunt, Texas	Kent, Michigan	Lenoir, North Carolina
Forest, Wisconsin	Gunnison, Colorado	Hunterdon, New Jersey	Kent, Rhode Island	Leon, Florida
Forsyth, North Carolina	Gwinnett, Georgia	Huntington, Indiana	Kenton, Kentucky	Lewis and Clark, Montana

Appendix Table A-3 - List of Counties in the Final Sample

Lewis, Washington	Mariposa, California	Montezuma, Colorado	Oldham, Kentucky	Pitt, North Carolina
Liberty, Florida	Marshall, Mississippi	Montgomery, Alabama	Oliver, North Dakota	Pittsburg, Oklahoma
Licking, Ohio	Marshall, Oklahoma	Montgomery, Arkansas	Olmsted, Minnesota	Placer, California
Limestone, Alabama	Marshall, Tennessee	Montgomery, Iowa	Oneida, New York	Platte, Missouri
Lincoln, Missouri	Martin, Florida	Montgomery, Kansas	Oneida, Wisconsin	Plumas, California
Lincoln, North Carolina	Martin, North Carolina	Montgomery, Maryland	Onondaga, New York	Plymouth, Massachusetts
Lincoln, Oklahoma	Mason, Michigan	Montgomery, North Carolina	Orange, California	Pointe Coupee, Louisiana
Linn, Iowa	Matanuska-Susitna, Alaska	Montgomery, Ohio	Orange, Florida	Polk, Arkansas
Linn, Kansas	Maui, Hawaii	Montgomery, Pennsylvania	Orange, New York	Polk, Florida
Litchfield, Connecticut	Maury, Tennessee	Montgomery, Tennessee	Orange, Texas	Polk, Iowa
Livingston, Illinois	Mayes, Oklahoma	Montgomery, Texas	Orangeburg, South Carolina	Polk, Texas
Livingston, Kentucky	McClain, Oklahoma	Montrose, Colorado	Orleans, Louisiana	Polk, Wisconsin
Livingston, Louisiana	McCracken, Kentucky	Morgan, Alabama	Osage, Oklahoma	Portage, Ohio
Logan, Illinois	McCurtain, Oklahoma	Morgan, Indiana	Osceola, Florida	Porter, Indiana
Logan, Ohio	McHenry, Illinois	Morgan, Kentucky	Oswego, New York	Posey, Indiana
Lorain, Ohio	McIntosh, Georgia	Morris, New Jersey	Ottawa, Michigan	Pottawatomie, Oklahoma
Los Alamos, New Mexico	McKenzie, North Dakota	Muhlenberg, Kentucky	Ottawa, Oklahoma	Powder River, Montana
Los Angeles, California	McLean, Illinois	Multnomah, Oregon	Ouachita, Louisiana	Preble, Ohio
Loudon, Tennessee	McLean, Kentucky	Murray, Georgia	Outagamie, Wisconsin	Prince Edward, Virginia
Loudoun, Virginia	McLennan, Texas	Muscogee, Georgia	Oxford, Maine	Prince George's, Maryland
Love, Oklahoma	McMinn, Tennessee	Muskegon, Michigan	Ozaukee, Wisconsin	Prince William, Virginia
Lucas, Ohio	Meade, South Dakota	Muskogee, Oklahoma	Page, Virginia	Providence, Rhode Island
Luna, New Mexico	Mecklenburg, North Carolina	Napa, California	Palm Beach, Florida	Pulaski, Arkansas
Luzerne, Pennsylvania	Medina, Ohio	Natrona, Wyoming	Palo Alto, Iowa	Pulaski, Kentucky
Lycoming, Pennsylvania	Meigs, Tennessee	Navajo, Arizona	Panola, Mississippi	Putnam, New York
Lyon, Minnesota	Mendocino, California	Navarro, Texas	Park, Colorado	Putnam, Tennessee
Lyon, Nevada	Merced, California	Neosho, Kansas	Parker, Texas	Racine, Wisconsin
Macomb, Michigan	Mercer, New Jersey	Nevada, California	Pasco, Florida	Randall, Texas
Macon, Illinois	Mercer, North Dakota	New Castle, Delaware	Passaic, New Jersey	Randolph, Illinois
Macon, North Carolina	Mercer, Pennsylvania	New Hanover, North Carolina	Paulding, Georgia	Randolph, North Carolina
Macoupin, Illinois	Merrimack, New Hampshire	New Haven, Connecticut	Pawnee, Kansas	Rensselaer, New York
Madera, California	Mesa, Colorado	New London, Connecticut	Pennington, South Dakota	Richland, Montana
Madison, Alabama	Miami, Ohio	Newport News city, Virginia	Penobscot, Maine	Richland, South Carolina
Madison, Illinois	Middlesex, Connecticut	Newton, Arkansas	Peoria, Illinois	Richmond, Georgia
Madison, Indiana	Middlesex, Massachusetts	Niagara, New York	Perry, Indiana	Riley, Kansas
Madison, Mississippi	Middlesex, New Jersey	Noble, Ohio	Perry, Kentucky	Rio Arriba, New Mexico
Madison, New York	Mille Lacs, Minnesota	Norfolk, Massachusetts	Perry, Missouri	Rio Blanco, Colorado
Madison, Ohio	Milwaukee, Wisconsin	Northampton, North Carolina	Perry, Pennsylvania	Riverside, California
Madison, Tennessee	Minnehaha, South Dakota	Northampton, Pennsylvania	Person, North Carolina	Roane, Tennessee
Madison, Virginia	Missaukee, Michigan	Northampton, Virginia	Philadelphia, Pennsylvania	Roanoke, Virginia
Mahoning, Ohio	Missoula, Montana	Nueces, Texas	Phillips, Montana	Rock Island, Illinois
Manatee, Florida	Mobile, Alabama	Oakland, Michigan	Pickens, South Carolina	Rock, Wisconsin
Manistee, Michigan	Moffat, Colorado	Obion, Tennessee	Pierce, Washington	Rockbridge, Virginia
Manitowoc, Wisconsin	Monmouth, New Jersey	Ocean, New Jersey	Pike, Georgia	Rockdale, Georgia
Marathon, Wisconsin	Mono, California	Oconee, South Carolina	Pike, Kentucky	Rockingham, New Hampshire
Maricopa, Arizona	Monongalia, West Virginia	Ohio, Kentucky	Pima, Arizona	Rockingham, North Carolina
Marin, California	Monroe, Missouri	Ohio, West Virginia	Pinal, Arizona	Rockingham, Virginia
Marion, Florida	Monroe, New York	Okaloosa, Florida	Pinellas, Florida	Rockland, New York
Marion, Indiana	Monroe, Pennsylvania	Oklahoma, Oklahoma	Piscataquis, Maine	Rockwall, Texas
Marion, Texas	Monterey, California	Okmulgee, Oklahoma	Pitkin, Colorado	Rosebud, Montana

Appendix Table A-4 - List of Counties in the Final Sample

Rowan, North Carolina	Snohomish, Washington	Tarrant, Texas	Warren, Mississippi	Yellowstone, Montana
Russell, Alabama	Solano, California	Taylor, Wisconsin	Warren, New Jersey	Yolo, California
Rutherford, Tennessee	Somerset, Maine	Tehama, California	Warren, Ohio	York, Maine
Rutland, Vermont	Somerset, Pennsylvania	Teton, Wyoming	Warren, Virginia	York, Pennsylvania
Sacramento, California	Sonoma, California	Tioga, Pennsylvania	Warrick, Indiana	York, South Carolina
Sagadahoc, Maine	Spartanburg, South Carolina	Tippecanoe, Indiana	Washington, Arkansas	Yuma, Arizona
Salt Lake, Utah	Spokane, Washington	Tolland, Connecticut	Washington, Kentucky	
San Benito, California	St. Bernard, Louisiana	Tompkins, New York	Washington, Maine	
San Bernardino, California	St. Charles, Louisiana	Tooele, Utah	Washington, Maryland	
San Diego, California	St. Charles, Missouri	Travis, Texas	Washington, Minnesota	
San Francisco; coext., California	St. Clair, Illinois	Trego, Kansas	Washington, Ohio	
San Joaquin, California	St. Clair, Michigan	Trigg, Kentucky	Washington, Oklahoma	
San Juan, New Mexico	St. Croix, Wisconsin	Trumbull, Ohio	Washington, Oregon	
San Juan, Utah	St. James, Louisiana	Tucker, West Virginia	Washington, Pennsylvania	
San Luis Obispo, California	St. John the Baptist, Louisiana	Tulare, California	Washington, Rhode Island	
San Mateo, California	St. Johns, Florida	Tulsa, Oklahoma	Washington, Utah	
San Miguel, Colorado	St. Joseph, Indiana	Tuolumne, California	Washington, Wisconsin	
Sandoval, New Mexico	St. Louis city, Missouri	Tuscaloosa, Alabama	Washoe, Nevada	
Sangamon, Illinois	St. Louis, Minnesota	Tuscarawas, Ohio	Washtenaw, Michigan	
Santa Barbara, California	St. Louis, Missouri	Tuscola, Michigan	Waukesha, Wisconsin	
Santa Clara, California	St. Lucie, Florida	Tyler, Texas	Wayne, Michigan	
Santa Cruz, California	St. Martin, Louisiana	Uinta, Wyoming	Wayne, New York	
Santa Fe, New Mexico	St. Mary, Louisiana	Uintah, Utah	Webb, Texas	
Santa Rosa, Florida	St. Tammany, Louisiana	Ulster, New York	Weber, Utah	
Sarasota, Florida	Stafford, Virginia	Umatilla, Oregon	Webster, Mississippi	
Saratoga, New York	Stanislaus, California	Union, New Jersey	Weld, Colorado	
Sauk, Wisconsin	Stark, Ohio	Union, North Carolina	West Baton Rouge, Louisiana	
Schenectady, New York	Ste. Genevieve, Missouri	Union, Ohio	Westchester, New York	
Schoolcraft, Michigan	Stearns, Minnesota	Union, South Carolina	Westmoreland, Pennsylvania	
Scott, Iowa	Steele, North Dakota	Union, South Dakota	Weston, Wyoming	
Scott, Kentucky	Steuben, New York	Utah, Utah	Wexford, Michigan	
Scott, Minnesota	Story, Iowa	Valencia, New Mexico	Whatcom, Washington	
Scotts Bluff, Nebraska	Strafford, New Hampshire	Van Buren, Arkansas	White Pine, Nevada	
Sedgwick, Kansas	Sublette, Wyoming	Van Buren, Iowa	Will, Illinois	
Seminole, Florida	Suffolk city, Virginia	Vanderburgh, Indiana	Williams, North Dakota	
Sequoyah, Oklahoma	Suffolk, Massachusetts	Ventura, California	Williamsburg, South Carolina	
Sevier, Tennessee	Suffolk, New York	Vernon, Wisconsin	Williamson, Tennessee	
Sharkey, Mississippi	Sullivan, New Hampshire	Victoria, Texas	Wilson, Tennessee	
Shasta, California	Sullivan, Tennessee	Vigo, Indiana	Windham, Connecticut	
Shawnee, Kansas	Summit, Ohio	Vilas, Wisconsin	Winnebago, Illinois	
Sheboygan, Wisconsin	Sumner, Kansas	Volusia, Florida	Winnebago, Wisconsin	
Shelby, Alabama	Sumner, Tennessee	Wabash, Indiana	Wood, Ohio	
Shelby, Indiana	Sumter, Alabama	Wake, North Carolina	Wood, West Virginia	
Shelby, Tennessee	Sumter, Georgia	Wakulla, Florida	Worcester, Massachusetts	
Sheridan, Wyoming	Sussex, Delaware	Walker, Alabama	Wright, Minnesota	
Sherman, Kansas	Sutter, California	Waller, Texas	Wyandotte, Kansas	
Simpson, Kentucky	Swain, North Carolina	Walworth, Wisconsin	Wythe, Virginia	
Siskiyou, California	Sweetwater, Wyoming	Ward, North Dakota	Yalobusha, Mississippi	
Skagit, Washington	Talladega, Alabama	Warren, Iowa	Yancey, North Carolina	
Smith, Texas	Taney, Missouri	Warren, Kentucky	Yavapai, Arizona	

Appendix B

Our data limitation and sample selection criteria remove a considerable portion of birth records. Indeed, our final sample consists of 1,270 counties for which we do have all atmospheric and pollution measures consistently reported for all months of the years the data is available. This limitation raises the concern that there could be characteristics in counties with data availability that make them systematically different than counties out of the sample and that these features may also play a role in driving the results. In Appendix Table B-1, we show mean value and standard deviation of selected maternal and county characteristics in the final sample versus in the original sample, i.e. the sample before merging with pollution data and the subsequent sample selections. Share of mothers with less than a college degree is 46.8 and 54.4 percent for the final and original samples, respectively. Thus, the final sample contains relatively better educated mothers. Moreover, per capita income in the final sample and original sample is roughly \$16.9K and \$13.7K, respectively. Therefore, we would expect parents with higher income to also be included in the final sample.

Our aim in this appendix is to explore whether the effects of pollution on birth outcomes is stronger/weaker among parents with better socioeconomic status and better education. We replicate the main results for the subsample of counties that are below-median county-level per capita income. The results are reported in Appendix Table B-2. Comparing the marginal effects and the implied percentage change from the mean of the outcomes with those of Table 4, one can observe larger impacts among relatively poorer counties in our final sample. In addition, we also replicate the main results for the subsample of low educated mothers. We report the results in Appendix Table B-3. We also find slightly larger effects in this subsample in comparison with the results of Table 4. Therefore, since the original sample is weighed towards lower income counties and lower educated parents, we can speculate that had we had available data for those counties we would have observed relatively larger impacts. The main results of the paper can be translated as a lower bound of the effects across the whole population.

Appendix Table B-1 - Selected Characteristics of Samples based on Data Availability

	Final Sample		Unavailable Data	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Age of Mother	26.96	2.635	25.864	3.488
Mother White	.56	.496	.665	.472
Mother Black	.287	.395	.222	.398
Mother’s Education Missing	.056	.207	.046	.196
Mother’s Education< High School	.024	.06	.024	.091
Mother’s Education=High School	.444	.23	.52	.311
Mother’s Education Some College	.244	.163	.241	.249
Mother’s Education Bachelor	.144	.134	.108	.177
Mother’s Education Master-PHD	.088	.107	.061	.134
Per Capita Personal Income, Real 1980	16990.459	4837.673	13726.002	3464.929
%Whites	83.508	14.491	85.658	17.247
%Blacks	12.108	13.821	11.127	16.134
Observations	775155		4712187	

Appendix Table B-2 - Replicating the Main Results among Low Income Counties

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel A.			
Ozone (STD)	-27.63212**	.00649*	.00169**	-16.58968*	-.37395**	-.16318**	.00142*
	(12.68908)	(.00334)	(.00081)	(9.65017)	(.17986)	(.08116)	(.0008)
Observations	251397	251397	251397	250080	251397	251397	251397
R-squared	.05299	.02901	.01484	.04329	.05603	-.01225	.01159
Mean DV	3305.402	0.066	0.012	3386.610	85.176	38.800	0.006
%Change	-0.836	9.827	14.117	-0.490	-0.439	-0.421	23.707
F-Stat	40.366	54.101	57.933	33.731	36.578	42.969	42.569
				Panel B.			
PM10 (STD)	-21.86802***	.0045**	.00131***	-14.87751***	-.25605**	-.14494***	.00113**
	(7.39138)	(.00212)	(.00049)	(5.64742)	(.11614)	(.04257)	(.00047)
Observations	180294	180294	180294	179131	180294	180294	180294
R-squared	.09959	.04544	.01983	.07328	.08888	.01542	.01682
Mean DV	3305.772	0.066	0.012	3387.467	85.149	38.816	0.006
%Change	-0.662	6.822	10.884	-0.439	-0.301	-0.373	18.855
F-Stat	32.446	49.461	53.851	26.774	31.970	32.508	43.340

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.
*** p<0.01, ** p<0.05, * p<0.1

Appendix Table B-3 - Replicating the Main Results among Low Educated Mothers

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
Ozone (STD)	-30.51443***	.00926***	.00231**	-18.85966**	-.50755***	-.13891**	.00186**
	(11.69315)	(.00354)	(.00108)	(8.79331)	(.19236)	(.0695)	(.00094)
Observations	187103	187103	187103	185729	187103	187103	187103
R-squared	.02855	.01002	.00566	.0298	.03124	-.00377	.00346
Mean DV	3260.349	0.076	0.014	3350.231	84.255	38.689	0.008
%Change	-0.936	12.181	16.475	-0.563	-0.602	-0.359	23.310
F-Stat	38.347	47.774	36.367	31.620	38.818	34.175	33.900
			Panel B.				
PM10 (STD)	-22.70654***	.0071***	.00152**	-13.29788*	-.32701**	-.12431**	.00163**
	(8.5126)	(.00215)	(.00064)	(6.79884)	(.13246)	(.05191)	(.00064)
Observations	155627	155627	155627	154321	155627	155627	155627
R-squared	.06355	.02122	.00914	.05494	.05859	.00522	.00539
Mean DV	3264.114	0.075	0.014	3353.618	84.304	38.711	0.008
%Change	-0.696	9.465	10.846	-0.397	-0.388	-0.321	20.423
F-Stat	41.802	45.504	31.130	32.553	36.961	25.517	22.191

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.
*** p<0.01, ** p<0.05, * p<0.1

Appendix C

In the paper, the pollution exposure measures are assigned based on the period of pregnancy. Moreover, we show the effects for exposure across different trimesters. We also show the effects during postnatal ages as a placebo test. In this appendix, we explore the effects of lagged values of pollution. The results are reported in two panels of Appendix Table C-1. We report the results for the lagged value (pre-prenatal period assignment) and the prenatal period value of pollutants. The main effects are concentrated on prenatal development period. Except for very low birth weight and very preterm birth, all the lagged values are statistically insignificant and economically quite small in magnitude. These results, combined with those of Table 7, suggest that the effects are primarily driven by exposure during pregnancy.

Appendix Table C-1 – Exploring the Sensitivity to Adding Lagged Values of Pollution

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
Lagged Ozone (STD)	5.3051	-.00253	-.00115*	4.03964	.036416	.02259	-.00018
	(4.1524)	(.00153)	(.00065)	(3.26531)	(.08949)	(.02105)	(.00013)
Ozone (STD)	-37.34916***	.0081***	.00253***	-28.55872***	-.72441***	-.11978***	.00199***
	(6.97986)	(.00204)	(.00072)	(6.48818)	(.13555)	(.04256)	(.00064)
Observations	515465	515465	515465	513893	515465	515465	515465
R-squared	.08851	.05514	.02785	.05602	.07041	.04511	.02291
Mean DV	3309.491	0.064	0.012	3388.886	85.258	38.811	0.006
F-Stat	59.202	71.435	156.019	54.319	61.456	74.741	134.976
			Panel B.				
Lagged PM10 (STD)	2.50621	-.00123	-.00087	2.80312	.11015	-.02013	-.00092*
	(5.54268)	(.00188)	(.00068)	(4.86719)	(.11036)	(.02864)	(.00053)
PM10 (STD)	-22.25927***	.00511***	.00217***	-14.99349***	-.38763***	-.09037***	.00164***
	(5.16567)	(.00165)	(.00062)	(4.37997)	(.0916)	(.02828)	(.0005)
Observations	374666	374666	374666	373281	374666	374666	374666
R-squared	.11314	.0717	.03432	.07427	.09243	.04512	.02701
Mean DV	3312.110	0.064	0.012	3391.191	85.277	38.833	0.006
F-Stat	60.121	64.618	154.711	48.445	55.613	61.167	117.397

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.
*** p<0.01, ** p<0.05, * p<0.1

Appendix D

In the main results, we focus on levels of pollution exposure variables and atmospheric measures. One concern is that the effects could be nonlinear and using OLS only provides a linear approximation of the true effects. Therefore, once we control for the nonlinearities in the effects, we may observe larger/smaller impacts. We address the potential nonlinearity in our measures by replacing both pollution and precipitation measures with the logarithm of the values. We replicate the main results using log values and report them in Appendix Table D-1. To interpret theses effects and compare them with those of Table 4, we use a one-standard-deviation change relative to the mean of pollutant based on values in Table 1. For instance, a 17.5 percent rise in ozone (6 unites (SD) relative to 29 units (mean)) is associated with about 15.9 grams lower birth weight (column 1, panel A, Appendix Table D-1). This effect is about 20 percent lower than that of reported in Table 4. Similarly, a one-standard-deviation change relative to the mean of PM10 is equivalent to roughly 32 percent change. This rise in PM10 is associated with roughly 14.9 grams lower birth weight (column 1, panel B, Appendix Table D-1). This change is about 23 percent lower than that of Table 4. Overall, the nonlinearities in the measures of pollution and our instruments may slightly overstate the effects.

Appendix Table D-1 – Exploring the Nonlinearity in Pollution Using Log Values

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
Ozone (STD)	-91.01341***	.02167**	.00368	-67.29479**	-1.85954***	-.24824	.002
	(31.26152)	(.0089)	(.0026)	(26.73985)	(.61677)	(.15395)	(.00218)
Observations	446175	446175	446175	444472	446175	446175	446175
R-squared	.08099	.05178	.02855	.05117	.06218	.04613	.02425
Mean DV	3307.467	0.065	0.012	3386.931	85.221	38.804	0.006
%Change	-2.752	33.338	30.632	-1.987	-2.182	-0.640	33.310
F-Stat	58.886	70.925	156.966	49.389	57.191	67.640	129.300
			Panel B.				
PM10 (STD)	-46.89303**	.01036**	.00293**	-27.50852	-.485	-.3461***	.00314**
	(20.75049)	(.00499)	(.00145)	(16.83688)	(.32431)	(.11972)	(.00138)
Observations	340284	340284	340284	338657	340284	340284	340284
R-squared	.12732	.07427	.0366	.0843	.10187	.05167	.02965
Mean DV	3310.485	0.064	0.012	3389.592	85.252	38.826	0.006
%Change	-1.417	16.188	24.408	-0.812	-0.569	-0.891	52.398
F-Stat	58.310	59.241	163.835	48.022	54.233	59.061	133.810

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.
*** p<0.01, ** p<0.05, * p<0.1

Appendix E

One may truly argue that the effects could be heterogeneous with regards to the level of urbanicity of a county. For instance, if the counties in our final sample are more located in metropolitan statistical areas with probably better access to jobs and healthcare, the effects could reveal a mitigate effects of pollution on birth outcomes. Hence, we would observe larger effects in areas that these mitigating channels are weaker. We explore this source of heterogeneity by interacting with the pollution measures a dummy of urbanicity that equals one if the county is located in an urban metro area with population of more than 100K and zero otherwise. The results are reported in Appendix Table E-1. We observe marginal effects that are quite similar to the main effects reported in Table 4. Therefore, we do not find a discernible heterogeneity in the effects across areas that are more/less urbanized.

Appendix Table E-1 – Heterogeneity by Urbanicity

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
Urban × Ozone (STD)	-17.31644***	.00366***	.00103***	-12.92155***	-.32921***	-.05912**	.00064*
	(4.99196)	(.00131)	(.0004)	(4.46204)	(.09095)	(.02853)	(.00034)
Observations	535036	535036	535036	532693	535036	535036	535036
R-squared	.08818	.05263	.02669	.05675	.06915	.04661	.02254
Mean DV	3309.772	0.064	0.012	3389.140	85.260	38.814	0.006
%Change	-0.523	5.717	8.603	-0.381	-0.386	-0.152	10.718
F-Stat	64.234	75.847	162.697	57.074	66.402	74.599	137.201
			Panel B.				
Urban × PM10 (STD)	-18.88979***	.00346**	.00125***	-12.09264**	-.25089**	-.11144***	.00123***
	(6.68477)	(.00168)	(.00047)	(6.0993)	(.1168)	(.0378)	(.00046)
Observations	392417	392417	392417	390266	392417	392417	392417
R-squared	.1107	.06879	.0331	.07243	.08986	.04404	.02648
Mean DV	3312.433	0.064	0.012	3391.491	85.278	38.837	0.006
%Change	-0.570	5.412	10.401	-0.357	-0.294	-0.287	20.443
F-Stat	65.676	66.457	160.746	52.052	60.720	64.913	125.225

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix F

In the paper, we aggregate pollution data from monitor-daily into county-monthly level. In this appendix, we validate our exposure measure by showing the association between the original monitor-daily data (for counties that are present in the final sample) and the county-monthly measures in the final sample. The results are reported in Appendix Table F-1**Error! Reference source not found.**. The marginal effects suggest strong and sizeable associations even after including county-month fixed effects. A one-standard-deviation rise in ozone and PM10 at the monitor-daily level is correlated with 0.37 and 0.50 standard-deviations change in the county-monthly measures, respectively.

Appendix Table F-1 - Relationship between Monitor-Daily Pollution and County-Monthly Pollution Data

	County-by-Month Pollution Exposure Measures as Outcomes:			
	PM10 (STD)		Ozone (STD)	
	(1)	(2)	(3)	(4)
PM10 (STD)	0.32148***	0.37554***		
	(0.03969)	(0.05144)		
Ozone (STD)			-0.45081***	0.50484***
			(0.08238)	(0.1205)
Observations	2226948	2226948	2255808	2255803
R-squared	0.95485	0.9573	0.9825	0.98639
County FE	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
County-Month FE	No	Yes	No	Yes

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions are weighted using the total number of births in each cell.
*** p<0.01, ** p<0.05, * p<0.1

Appendix G

Another important pollutant with potentially higher penetration into lungs is particulate matters less than 2.5 μm, or $PM_{2.5}$ (Liang et al., 2022; Liang et al., 2019; Lubczyńska et al., 2017; Xiao et al., 2018). As an additional analysis to complement the results of the paper, we use the same empirical method and use average county-level $PM_{2.5}$ as the endogenous pollutant. The results are reported in Appendix Table G-1. We observe consistently larger impacts across all birth outcomes compared with the effects of PM_{10} or ozone. For instance, a one-standard-deviation rise in $PM_{2.5}$ is associated with about 54 grams lower birth weight, roughly 2.6 times that of the effects of PM_{10} or ozone.

Appendix Table G-1 - Replicating the Main Results Using $PM_{2.5}$ as the Endogenous Pollutant

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PM_{2.5}$ (STD)	-54.26724***	.01509***	.0065***	-27.71603***	-1.02494***	-.18955***	.00394**
	(12.30111)	(.0051)	(.00223)	(10.00219)	(.27204)	(.05317)	(.00164)
Observations	193637	193637	193637	192506	193637	193637	193637
R-squared	-.09391	-.01608	-.04815	-.00174	-.05052	-.083	-.02865
Mean DV	3294.338	0.065	0.012	3373.479	85.036	38.736	0.006
%Change	-1.647	23.211	54.199	-0.822	-1.205	-0.489	65.604
F-Stat	844.591	572.316	306.840	579.772	729.559	399.378	232.730

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.
*** p<0.01, ** p<0.05, * p<0.1

Appendix H

One important source of seasonal pollution is wildfire smokes. A strand of literature in various disciplines examine the impact of wildfire smoke on birth outcomes (Amjad et al., 2021; Brown et al., 2022; Evans et al., 2022; Heft-Neal et al., 2022; Rangel & Vogl, 2019). Since precipitation is also seasonal, one could argue that wildfire smokes may confound the results. In Appendix Table H-1, we replicate the main results adding a set of county by year-month measures of wildfire smokes.[10] Although we observe small reductions in the marginal effects relative to the main results, the effects remain statistically and economically meaningful.

[10] This data is extracted from https://www.kaggle.com/datasets/rtatman/188-million-us-wildfires.

Appendix Table H-1 - Replicating the Main Results Controlling for County-Level Wildfire Smokes

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Panel A.				
Ozone (STD)	-17.86311***	.00315**	.00109***	-12.92633**	-.36879***	-.04647	.00072**
	(5.6558)	(.00131)	(.00039)	(5.15331)	(.10189)	(.0301)	(.00035)
Observations	525138	525138	525138	522877	525138	525138	525138
R-squared	.08769	.05334	.02641	.05747	.06747	.04974	.02228
Mean DV	3309.712	0.064	0.012	3389.061	85.261	38.812	0.006
%Change	-0.540	4.928	9.070	-0.381	-0.433	-0.120	12.037
F-Stat	52.353	78.480	127.094	44.342	48.932	69.238	112.780
			Panel B.				
PM10 (STD)	-19.57911***	.00339**	.00137***	-12.57575**	-.30463**	-.09538***	.00127***
	(6.63679)	(.00161)	(.00047)	(6.36289)	(.11883)	(.03668)	(.00041)
Observations	380439	380439	380439	378392	380439	380439	380439
R-squared	.11283	.06902	.03278	.07503	.09065	.05063	.02646
Mean DV	3312.382	0.064	0.012	3391.363	85.277	38.836	0.006
%Change	-0.591	5.303	11.427	-0.371	-0.357	-0.246	21.121
F-Stat	47.681	59.850	137.820	36.671	42.201	52.532	108.721

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level temperature and humidity. The regressions are weighted using the total number of births in each cell.
*** p<0.01, ** p<0.05, * p<0.1

Appendix I

The exclusion restriction assumption in the identifications strategy of the paper requires that the instruments do not have a direct impact on the outcomes except through changes in the endogenous regressors. To show that this is the case, we explore the direct association between precipitation and birth outcomes, controlling for pollution variables of interest. The results are reported in Appendix Table I-1. We do not observe a link between precipitation and infants' health once we implement a full model. The marginal effects are very small in magnitude and statistically insignificant.

Appendix Table I-1 - The Direct Link between Precipitation and Birth Outcomes

	Outcomes:						
	Birth Weight	Low Birth Weight	Very Low Birth Weight	Full-Term Birth Weight	Fetal Growth	Gestational Weeks	Very Premature Birth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Precipitation (STD)	1.04937	-.00025	-.00011	.89128	.02041	-.04647	.0002
	(.76771)	(.0002)	(.00008)	(.71388)	(.02199)	(.0301)	(.0005)
Observations	341539	341539	341539	341261	341539	341539	341539
R-squared	.64949	.27409	.11169	.66887	.64123	.04974	.02228
Mean DV	3313.020	0.064	0.011	3391.935	85.323	38.812	0.006
%Change	0.047	-0.392	-1.136	0.029	0.030	-0.120	3.037

Notes. Standard errors, clustered at the county level, are in parentheses. The regressions include mother's race dummy, child gender dummy, county-by-month fixed effects, and year-by-month fixed effects. The regressions also include average county-level parental controls including mother education (five categories), mother age, father race being white, father's ethnicity, smoker mothers, father age (10 categories), and prenatal visits. All regressions contain controls for county-level pollution, temperature, and humidity. The regressions are weighted using the total number of births in each cell.

*** p<0.01, ** p<0.05, * p<0.1