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Same Environment, Stratified Impacts? Air Pollution, Extreme Temperatures, and Birth Weight in Southeast China

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Abstract

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Linking 54,828 singleton live birth records from a district in Guangzhou, China to ambient air pollution (PM10 and a composite measure) and extreme temperature data, we test whether, overall, maternal education is an "effect modifier" in the relationships between ambient air pollution, extreme temperature, and birth weight. Via conditional quantile regressions, we then test for effect heterogeneity according to the underlying physical vulnerability of babies—those further to the left in the conditional distribution of birth weight—after conditioning on other confounders. Results show that the protection associated with a college-educated mother with respect to pollution and extreme heat is substantial: up to 0.31 standard deviations of birth weight. Importantly, this protection is amplified under more extreme ambient conditions and for physically vulnerable infants, after conditioning on other confounders.

Keywords

air pollution, temperature, China, birth outcomes, infants, maternal education

Disciplines

Demography, Population, and Ecology | Family, Life Course, and Society | Gender and Sexuality | Inequality and Stratification | Place and Environment | Social and Behavioral Sciences | Sociology

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January 4, 2021

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1 Introduction

Ambient environmental conditions, including both air pollution and temperature, have been associated with adverse birth outcomes in a number of settings, though findings for temperature remain limited (Shah and Balkhair 2011; Stieb et al. 2012; Klepac et al. 2018; Melody et al. 2019; Cho 2020; Kloog et al. 2015; Zhang, Yu, and Wang 2017). There is some suggestive evidence that lower socioeconomic status groups, defined by occupation or education, might be distinctly vulnerable to the ill effects of air pollution or extreme temperatures, but there is a need for additional studies to consider possible mitigation of negative effects by maternal education (see Basu et al. (2018) and Son et al. (2019) for contradictory findings on temperature and birth weight; for a review of findings on pollution and low birth weight, see Westergaard et al. (2017)). Babies of less-educated mothers may be more vulnerable compared to those of more-educated mothers to the same air pollution or temperature conditions if their mothers lack access to living, work, transportation, and leisure spaces with indoor heating and cooling systems or air filtration systems, or if they lack knowledge of or resources for mitigation strategies and practices. Protection associated with maternal education might emerge more strongly under higher risk conditions—not only in more extreme ambient conditions, but also for babies with more significant underlying physical vulnerabilities. Little research has addressed whether the protective effects of education might be heterogeneous with respect to the underlying physical vulnerabilities of babies.[1]

This paper investigates two questions. First, do expectant mothers in common ambient pollution and temperature environments experience different birth outcomes, according to their education? In other words, are there protective effects of maternal education? Second, are protective effects of maternal education more pronounced among the most physically vulnerable babies? We focus on birth weight as the outcome of interest. Birth weight is a consistent correlate of health and other socio-economic outcomes across the life course (Behrman and Rosenzweig 2004; Black, Devereux, and Salvanes 2007; Behrman, Xiong, and Zhang 2015; Torche and Conley 2016). We utilize a database of every singleton live birth recorded every

1. One prior study investigated both socioeconomic status and underlying physical vulnerability of babies in Korea (Lamichhane et al. 2020).

day in one city district in southeast China between 2009 and 2011, for a total of 54,828 birth records, linked to daily air pollution and meteorological data spanning the entire prenatal periods for these births. We work backwards from date of birth and gestational age to calculate date of conception and generate accumulated potential exposure estimates for three monitored air pollutants, namely particulate matter (PM_{10}), sulfur dioxide (SO_2), and nitrogen dioxide (NO_2), and generate a composite index of potential exposure to all three air pollutants. We also calculate the percentage of days in each pregnancy that were extreme hot or cold days.

To address our main research questions, we interact maternal educational category with pollution and extreme temperature measures to estimate effect modifications—protective effects—associated with maternal education, after adjusting for infant sex, a quadratic function of maternal age, parity, urban residence, rainfall, and time trends. Conditional on ambient temperature exposures, we find that one standard deviation increase in ambient PM_{10} is associated with a 0.28 standard deviation reduction in birth weight. Furthermore, we find that at average ambient PM_{10} and extreme temperature exposure levels, the protective effect of college education amounts to up to 0.08 standard deviations of birth weight.

Further, we allow for the protective effects of maternal education to be heterogeneous across conditional quantiles. Following the literature on conditional quantile estimation (Abrevaya 2001; Arias, Hallock, and Sosa-Escudero 2001; Koenker and Hallock 2001; Abrevaya and Dahl 2008; Hao and Yeung 2015), conditional on observed maternal characteristics, time trends, and environmental exposures, we interpret newborns to the left of the conditional distribution of birth weight as having higher levels of unobserved underlying physical vulnerabilities. We find that at lower conditional quantiles, a one standard deviation increase in ambient PM_{10} is associated with a reduction in birth weight of up to 0.48 standard deviations. The protective effect of college education can be up to 0.31 standard deviations of birth weight when children with higher unobserved underlying physical vulnerabilities—those at lower conditional quantiles—face high levels of ambient PM_{10} and extreme temperature exposures.

2 Background and Research Questions

2.1 Air Pollution and Birth Outcomes

Studies have traced associations between prenatal exposure to various kinds of air pollutants and adverse birth weight and other birth outcomes (Shah and Balkhair 2011; Stieb et al. 2012; Klepac et al. 2018; Melody et al. 2019). Several recent reviews have synthesized findings. Melody et al. (2019) conducted a systematic review of acute air quality change studies and found mixed results: there is some evidence that maternal exposure to acute changes in air quality of short-to medium-term duration increases the risk of fetal growth restriction and preterm birth, but the relationship for other adverse obstetric or neonatal outcomes is less clear. Shah and Balkhair (2011) conducted a broader systematic review of studies of air pollution exposure and birth outcomes. This review suggested that maternal exposure to sulfur dioxide was associated with preterm birth, exposure to $PM_{2.5}$ was associated with low birth weight, preterm birth, and small-for-gestational-age birth, and exposure to PM_{10} was associated with small-for-gestational-age birth. Evidence for NO_2 was inconclusive.

Another systematic review and meta-analysis of 62 studies indicated that pooled estimates of effects generally suggest associations between carbon monoxide (CO), NO_2, and particulate matter and pregnancy outcomes, but also that there was a high degree of heterogeneity among studies (Stieb et al. 2012). Hao et al. (2016) analyzed birth records between 2002 and 2006 from the Georgia Department of Public Health and found that all traffic-related pollutants, including NO_2 and $PM_{2.5}$, were associated with preterm birth. A large-scale study in Brisbane, Australia indicated that pregnant exposures to $PM_{2.5}$, SO_2, NO_2, and ozone (O_3) were associated with increased risks of low birth weight, as well as pre-term birth (Chen et al. 2018).

Focusing on particulate matter, a recent national study for the United States analyzed birth certificates data for the period 1999 to 2007 and found significant birth weight effects associated with gestational exposures to one form of coarse particulate matter ($PM_{10\text{-}2.5}$) (Ebisu, Berman, and Bell 2016). Similarly, a study of 7,772 mothers enrolled in a prospective study in the Netherlands between 2001 and 2005 found that PM_{10} exposure during pregnancy was inversely associated with birth weight (Hooven et al. 2012). The World Health Organization Global

Survey on Maternal and Perinatal Health study examined whether outdoor $PM_{2.5}$ was associated with adverse birth outcomes among 22 countries from 2004 through 2008 (Fleischer et al. 2014). Results showed that across all countries, $PM_{2.5}$ was not associated with preterm birth, but was associated with low birth weight. In China, the country with the greatest $PM_{2.5}$ range among those studied, preterm birth and low birth weight both were associated with the highest quartile of $PM_{2.5}$ (Fleischer et al. 2014). PM_{10} and $PM_{2.5}$ concentrations are highly correlated in China—especially in southern China (Zhou et al. 2016). Studies in Lanzhou, China and Wuxi, China also indicate that prenatal exposure to PM_{10} increases risk of preterm birth (N. Zhao et al. 2015; Han et al. 2018).

A recent paper systematically reviewed Chinese and English publications on links between air pollution exposure and adverse pregnancy outcomes in China (Jacobs et al. 2017). The authors reported that SO_2 was consistently associated with lower birth weight and more preterm births and PM_{10} was consistently associated with congenital anomalies, especially cardiovascular defects. Results for NO_2 were inconsistent, and the authors concluded that further studies were required on the effects of $PM_{2.5}$, ozone (O_3) and carbon monoxide (CO). While a number of the studies adjusted for education (or other measures of socioeconomic status), the review does not report tests of effect modification across these stratifiers. A more recent study in Guangdong Province (Liu et al. 2019), which covered the period of 2014 to 2015, reported, among other significant findings, significant associations with low birth weight for $PM_{2.5}$, PM_{10}, SO_2, NO_2, and O_3 in the first month and with $PM_{2.5}$, PM_{10}, NO_2, and O_3 in the last month of pregnancy.

2.2 Extreme Temperature and Birth Outcomes

While weather patterns and pollution intensity tend to be associated, temperature itself may be linked to birth outcomes. This relationship is one of rising global significance, as extreme temperature events are increasing in frequency, duration, and magnitude (World Health Organization 2018b). For example, between 2000 and 2016, the number of people exposed to heat waves increased by around 125 million (World Health Organization 2018b). However, to date, evidence remains limited (Kloog et al. 2015; Zhang, Yu, and Wang 2017; Basu et al. 2018), and that which is available is somewhat mixed. For example, a recent analysis of data from Korea found no significant temperature effect on birth outcomes (Cho 2020). A systematic review published in 2017 concluded that the evidence linking preterm birth and low birth weight to ambient temperature was still very limited and not yet conclusive, though there were more examples of adverse estimated effects for high temperatures than for low temperatures (Zhang, Yu, and Wang 2017). A second systematic review published in 2020 covered papers about the associations of air pollution and heat exposure with preterm birth, low birth weight, and stillbirth in the United States (Bekkar et al. 2020). Only three papers were identified that considered heat and birth weight, but all found significant risk. One, a paper that analyzed 220,572 singleton births for the years 2002 to 2008 from 12 US sites, found that whole-pregnancy cold or hot temperature increased term low birth weight risk (Ha et al. 2017). A second paper, conducted among 43,629 full-term but low birth weight babies and 2,032,601 normal-weight babies in California for the period 1999 to 2013, found that higher long-term apparent temperature exposure was associated with term low birth weight (Basu et al. 2018). The third reviewed paper, conducted among births in Massachusetts from 2000 through December 2008 (Kloog et al. 2015), showed decreased birth weight with increased air temperature. Finally, a study in the city of Guangzhou found that exposure to either low or high temperatures during pregnancy was associated with an increased risk of preterm birth (He et al. 2016).

2.3 Same Ambient Environment, Different Impacts

There is at least suggestive evidence that the same ambient environment might be experienced differently for more and less economically vulnerable groups, such as groups defined by parental education.[2] Hao et al.'s (2016) Georgia study found that associations of traffic-related pollutants, including NO_2 and $PM_{2.5}$, with preterm birth tended to be stronger for mothers with low educational attainment. A study in Korea of multiple air pollutants showed mixed results, but some evidence of socioeconomic disparity in the effects of full-pregnancy exposure at the lowest conditional quantiles of birth weight (Lamichhane et al. 2020). Heo, Fong, and Bell (2019) conducted a systematic review of papers assessing effects of particulate matter on birth outcomes

2. Positive associations between maternal education and birth outcomes, including birth weight but also preterm birth and birth length, have been described in a number of studies (Abel, Kruger, and Burd 2002; Ballon et al. 2019).

from 2000 to 2019 and found suggestive evidence that the risk posed was greater for babies of mothers with lower educational attainment for preterm birth and low birth weight.

However, in a recent review of epidemiological literature about ambient air pollution and birth weight, Westergaard and her colleagues (2017) identified only a small number of studies that addressed effect modification by maternal education status. With regard to temperature effects, Zhang, Yu, and Wang (2017) call for more attention to the possibility of individual effect modifiers; maternal education is one important potential stratifier (see Basu et al. (2018) and Son et al. (2019) for inconsistent findings on maternal education as an effect modifier). Generally, the resources associated with maternal education might be more likely to be brought to bear under extreme conditions of pollution and temperature, which would exacerbate the maternal protective effect under these conditions. A similar logic suggests that the protective effects of maternal education with respect to pollution and extreme temperature might be most pronounced for more physically vulnerable infants.

While we have not found other studies of pollution and birth weight that investigate variability in the protective effect of maternal education using a conditional quantile approach, it is important to acknowledge that a handful of studies in the United States have used this approach to consider heterogeneous vulnerability to ambient pollution exposure. A study of $PM_{2.5}$ in California (Schwarz et al. 2019) shows a tendency of somewhat larger negative associations with outcomes at the lowest conditional quantiles, though primarily among the Non-Hispanic Black population. A study of $PM_{2.5}$ in Massachusetts (Fong et al. 2019) found that the negative association between $PM_{2.5}$ and birthweight was larger in magnitude at the lower conditional quantiles of birthweight than those at the higher end. In contrast, a study in Atlanta (Strickland et al. 2019) showed larger effects for several pollutants at higher conditional quantiles. While results are mixed, all of these studies suggest the potential value in testing for heterogeneity in associations across the conditional distribution of birthweight.

2.4 Research Questions

Using a case study of three years of singleton live births in one district in Guangzhou, China, we study the protective effect of mothers' education with respect to pollution exposure. Specifically, we consider the association between expectant mothers' college educational attainment and their children's birth weights and allow the college educational gradient to be heterogeneous at different ambient pollution and extreme temperature levels. By including pollution and extreme temperature in the same specifications, we are able to isolate the separate relationships between these correlated but distinct ambient environmental factors and birth outcomes. Conditional on environmental exposures, we also allow the educational gradient to be heterogeneous for children with different underlying unobserved vulnerabilities.

Our analysis relaxes the restrictions imposed by common regression frameworks on how socioeconomic factors might impact child-birth outcomes in a setting where mothers are exposed to high levels of negative environmental factors, including pollution. A common regression framework includes educational status as an additive variable (for example, see Koenker and Hallock (2001) in the context of quantile regressions; Bharadwaj and Eberhard (2008) in the context of mean regressions). In the context of (conditional) mean regressions, this framework means that the educational gradient in birth weight is constant across levels of environmental exposure levels. By interacting mothers' education with multiple potential negative environmental factors, we allow for the educational gradient in child birth outcomes to be magnified at different rates depending on how negative environmental factors jointly worsen. Furthermore, by estimating education-environment interactions separately at different conditional quantiles of birth weight, we allow the educational gradient to have different slopes by quantiles of unobserved underlying physical vulnerabilities of babies. The rich heterogeneous relationships allow for a nuanced look at the potential protective effects of socio-economic status—as proxied by maternal college education—in ameliorating the effects of negative environmental factors.

3 Data and Methods

3.1 Study Site

The study site for this project is Guangzhou, which is the capital city of Guangdong Province in southeast China, in the Pearl River Delta. Guangzhou, along with several other cities in Guangdong as well as Hong Kong and Macau, is part of the rapidly-developing "Greater

Bay Area" megalopolis. The region is wealthy, with Shenzhen and Guangzhou, respectively, ranked third and fourth highest in city GDP in China, after Beijing and Shanghai (Buchholz 2019). Guangzhou has a typical subtropical climate, with very mild winters and hot, humid summers. The annual mean temperature in Guangzhou is around 22 degrees Celsius (Climate-Data.org 2020). While south China has had less air pollution than north China, as an economic development center, Guangzhou has been one of the most polluted cities in the region—especially before 2010. Importantly, Guangzhou has a well-established and extensive air-quality monitoring system with both air pollution indices and individual pollutant concentrations available at the city level.

Figure 1 shows levels of air pollution in Guangzhou from 2008 to 2011 for three monitored pollutants: PM_{10}, SO_2, and NO_2. The levels of pollution depicted in Figure 1 reflect substantial improvements in Guangzhou's air quality compared to prior years. In the early 2000s, the local government implemented progressive air-quality control efforts that included closing down low-efficiency coal power plants and enforced installation of desulfurization facilities (Zhong et al. 2013). Even with improvements, annual mean air pollution in Guangzhou during this period exceeded the World Health Organization standard for PM_{10}: a 20 μg/m3 annual mean. Further, 66.4% of days surpassed the 24-hour mean standard for PM_{10} of 50 μg/m3 and 76% of days surpassed the SO_2 standard of 20 μg/m3 (World Health Organization 2018a). There is strong seasonality in all three types of air pollution, with more severe air pollution in the winter than in the summer.

3.2 Data

We link three forms of data for this analysis: birth certificate data, air pollution data, and meteorological data.

3.2.1 Birth Certificate Data

We use birth certificate data representing all births that took place in a district in the city of Guangzhou on every day in the years 2009 to 2011. It is the responsibility of the parents or the family concerned to register all births within 15 days after birth (Lin et al. 2015). Birth certificate data include information about gestational age based on reported last menstrual period and confirmed by ultrasound scanning, stillbirth, birth weight, birth length, sex, parity, Apgar scores, and mother's age, education, occupation, rural/urban residence and number of pregnancies.[3]

3.2.2 Air Pollution Data

Our data source for air pollution is the Guangzhou Environmental Bureau, which reports the daily average levels of three monitored "criteria": air pollutants (PM_{10}, NO_2, and SO_2) at the city level during the period 2005 to 2011. These pollutants are measured according to National Standard (*Guo Biao)* GB3095—1996.[4] These are the only three pollutants for which data were collected until 2014.

3.2.3 Meteorological Data

We used the universal thermal climate indices (UTCI) from Copernicus and the European Centre for Medium-Range Weather Forecasts to measure extreme temperatures (Copernicus and European Centre for Medium-Range Weather Forecasts 2020). The UTCI, a thermal comfort indicator based on human heat balance models, is designed to be applicable in all seasons and climates and for all spatial and temporal scales (Copernicus and European Centre for Medium-Range Weather Forecasts 2020). The UTCI is a one-dimensional index that reflects "the human physiological reaction to the multidimensionally defined actual outdoor thermal environment" (Bröde et al. 2012, 481). Scores can be classified into ten thermal stress categories, ranging from extreme cold stress to extreme heat stress (Copernicus and European Centre for Medium-Range Weather Forecasts 2020). In a subtropical, humid environment such as Guangzhou, this index provides a wider range of variation than ambient temperature. Finally, we use 24-hour accumulated rainfall for Guangzhou for the same period, calculated from observed rainfall data (original source: National Oceanic and Atmospheric Administration (2020); as provided by Raspisaniye Pogodi Ltd. (2020)).[5]

3. Birth certificates also contain information on infant health and neonatal mortality.

4. There is precedent for using city-average measures of pollution. N. Zhao et al. (2015) report seven studies that used city-level averages of PM_{10} (Sagiv et al. 2005; Hansen et al. 2006; Jiang et al. 2007; Darrow et al. 2009; Suh et al. 2009; Q. Zhao et al. 2011; Schifano et al. 2013).

5. We provide details on how we acquire and process ECMWF data in Appendix B.

3.3 Analytic Sample

We begin with birth certificate data for all live births (67,108 or 99.1% of all births) in the district for the period 01 January 2009 to 31 December 2011. To avoid fixed cohort bias,[6] we delete births within this period with conception dates earlier than 14 July 2008 and those with conception dates later than 15 February 2011 (as gestational age varies between 171 and 319 days), which leaves 58,827 observations. We exclude observations with birth weight less than 500g (17 observations dropped), or birth length less than 28 centimeters or longer than 100 centimeters (51 observations dropped). We further restrict our sample to include only those with observed gestational age (855 observations without gestational age dropped) and only live singleton births.[7] In the end, our analytic sample is 54,828 live singleton births (15,459 born in 2009, 20,697 born in 2010, and 18,672 born in 2011)

3.4 Measurement

Table 1 contains summary statistics for all variables employed in the analysis. Below, we describe our variables.

3.4.1 Birth Weight

Birth weight is reported in grams. The mean birth weight is 3,181 grams and the standard deviation is 473 grams. Mothers with a college degree on average have 47 grams (p=0.00) higher birth weight than mothers with at most a high school degree.

6. Fixed cohort bias emerges when a sample consists of births during a fixed period—this approach will include only longer pregnancies at the start of the study and only the shorter pregnancies at the end of the study. This has the potential to bias studies of environmental exposures (Strand, Barnett, and Tong 2011).

7. Because there is no information on the number of multiple births, we count duplicate observations in terms of all observed maternal and paternal characteristics (including mother's birthdate, parity, number of previous pregnancies, urban/rural residence, maternal occupation, maternal education, paternal education, gestational age, indicator of high risk levels) as well as birthdate of the baby, and treat the observations with one duplicated case as twins (3.90% of 57,108 observations) and those with two duplicated cases as triplets (0.08% of 57,108 observations) and those with four duplicated cases as quintuplets (0.01% of 57,108 observations).

3.4.2 Air Pollution

We obtained data on three criteria pollutants, PM_{10}, NO_2 and SO_2, measured at the city average level, from the Guangzhou Environmental Bureau. A small number of observations with missing data were replaced with moving averages for the 4 preceding and following days. Between the years 2009 and 2011, by our estimates, Guangzhou's air pollution far exceeded the safety standards set by the WHO, with annual mean concentrations of PM_{10} of 76.8 μg/m3 in 2008, 76.8 μg/m3 in 2009, 71.1 μg/m3 in 2010 and 70.0 μg/m3 in 2011. The World Health Organization safety standard for PM_{10} is that the annual mean should not exceed 20 μg/m3 (World Health Organization 2018a). Seasonal variation is especially significant. For example, the daily mean for PM_{10} is 50.02 μg/m3 in July, on average, but 105.86 μg/m3 in December, during the period covered by this study.

To calculate potential exposure estimates for each birth, we define each mother's gestational period by subtracting the gestational age from the birth date. We then summarize over the duration of pregnancy the daily average level of each pollutant to calculate the accumulated total potential exposure during pregnancy for each individual. However, this approach suffers from a potential problem—it generates a spurious inverse correlation between adverse birth outcomes and accumulated air pollution levels because a shorter gestational age implies a shorter pregnancy and therefore smaller accumulated air pollution exposure. We avoid this spurious relationship by dividing the accumulated levels of each pollutant during pregnancy by each woman's pregnancy duration to get a daily mean level of exposure during pregnancy.

Because pollutants tend to co-vary, we conduct principal component analysis of the three pollutants' daily mean potential exposures during pregnancy and adopt the first principal component, which accounts for 86% of the total variance, as a composite index of pollution. We focus on results for our particulate matter measure—PM_{10}—in the main text, and comment briefly on similar findings using the composite pollution index. Detailed results using the composite measure are included in an Appendix.

Substantial individual variation in potential pollution exposure comes from variation in pregnancy timing. As pollution is usually higher in winter than in summer, those whose pregnancy occurs mainly in the winter have higher pollution exposure than those whose pregnancy occurs mainly in the summer. Moreover, pregnancies in earlier years on average have higher potential pollution exposure than those in later years, as a result of air quality improvement over time. In the Guangzhou data, there is an apparently counterintuitive pattern in which mothers with at least a college degree have higher potential air pollution exposure than mothers with at most a high school degree (as shown in Table 1). This pattern emerges because mothers with at most a high school degree, a category that includes many migrant workers from rural areas, are more likely to marry and conceive in January and February, around Chinese New Year. Figure 2 shows that, after controlling for conception year-by-month fixed effects, the distributions of ambient air pollution exposure are not significantly different between the two maternal education groups.[8]

3.4.3 Extreme Temperature

We set a cutoff for defining extreme temperatures by creating a local reference dataset comprised of the nine years of records of daily mean UTCI that immediately preceded the dates of our study. We define extreme low and high temperatures, respectively, by generating cut-points marking the bottom 1 percent of the distribution of the reference dataset, at -2.4 degrees Celsius, and the top 1 percent of the reference dataset, at 34.5 degrees Celsius. Each woman's exposure to extreme temperatures is defined by the proportion of days during pregnancy with daily mean UTCI under or above the cut-off temperatures. Extreme cold and hot temperatures defined in this way correspond to ECMWF categories of moderate cold stress (defined as -13 to 0 degrees Celsius) and strong heat stress (defined as 32 to 38 degrees Celsius). Although air conditioning had become widespread in Guangzhou by the time of the study period, heating in winter was not widely available, which is important for understanding any observed effects of cold stress in this region. Using this definition, pregnant women in the sample spent 0.89% of their pregnancy duration (2.4 days) exposed to extreme cold and 1.19% of the duration of pregnancy (3.2 days) exposed to extreme heat, on average.

We perform sensitivity analyses with a less stringent definition of extreme temperatures, using a 2.5 percent cutoff to define extreme cold and extreme heat (at 0.33 degrees Celsius and

8. Individuals with different SES may vary in ability to choose where to live and work based on air quality and to take mitigation against air pollution, for example, by wearing masks or installing air filter. However, the available data do not permit measurement of the realized individual air pollution exposure, and the spatial variation in individual air pollution exposure.

33.76 degrees Celsius, respectively). Using this alternative definition, pregnant women in the sample spent 2.44% (6.6 days) of the pregnancy duration in extreme cold and 2.79% of the pregnancy duration (7.6 days) in extreme heat. Table 2 presents additional distributional details of the extreme heat and cold measures.

3.4.4 Maternal Education

We code *mothers' education* in two categories: high school and below (0) and college and above (1). In our analytic sample, 18,067 (33%) report college attainment. This sample of mothers from the center of the most developed metropolitan city in South China is highly educated compared to the population in Guangdong Province as a whole (14% of the female population reported with tertiary attainment) and roughly on par with figures for China's wealthiest province-level cities (Beijing, 38%, and Shanghai, 31%) (Center for Strategic and International Studies 2020).

3.4.5 Control Variables

Pregnancy risks associated with advanced maternal age are well established for mother and child, and include heightened risk of pre-term labor, fetal growth restriction, and fetal demise among those over 35, in comparison to younger mothers (Sauer 2015).[9] Pregnancy when young also tends to be associated with risk, but often for social rather than biological reasons. To capture non-linear age effects, we include continuous controls for *maternal age* and *maternal age squared*. We adjust for *sex of the child* (0 if male, 1 if female) and *parity* (with a set of binary dummy variables). We also include controls for *urban residence status* (0 if rural, 1 if urban), and *conception year by month* fixed effects to control for seasonal effects and any time trend, as well as *day of the week at birth* fixed effects, as cesarean sections are more likely to be scheduled during weekdays. Finally, we adjust for *daily mean rainfall* during the duration of pregnancy using a cubic function of daily mean rainfall in all regressions to model the nonlinear relationship between rainfall and birth weight.

9. We have found few studies that identify whether advanced maternal age places mothers at particular risk to conditions of air pollution exposure. However, one cohort study in Wuxi, China showed an effect modification with maternal age: preterm birth risk associated with exposure to high levels of PM_{10} occurred primarily among women over age 35 (Han et al. 2018).

3.5 Analytic Approach

We model birth weight as related to maternal education, air pollution and extreme temperature exposure in both mean and quantile regression frameworks. We first estimate a baseline main effects (conditional) mean regression model:

$$
\begin{aligned}
\text{Birthweight}_{\text{ymi}} = {} & \alpha + \zeta_{ym} + \sigma_0 \text{Edu}_i \\
& + \gamma_1 P_i + \gamma_2 \text{Cold}_i + \gamma_3 \text{Heat}_i \\
& + g\left(\text{Rainfall}_i\right) + \mathbf{X}_i \theta^{'} + \varepsilon_i \,,
\end{aligned} \tag{1}
$$

where $\text{Birthweight}_{\text{ymi}}$ is birth weight of individual i who is conceived in year y and month m. Edu_i is a binary variable indicating if a mother has at least a college degree. P_i is a continuous variable measuring each mother's prenatal ambient exposure to PM_{10}, or the composite index of PM_{10}, NO_2 and SO_2. Cold_i and Heat_i are continuous variables measuring the percentages of prenatal days exposed to extreme cold or heat. $g\left(\text{Rainfall}_i\right)$ is a cubic function of daily mean precipitation that a mother is exposed to during her pregnancy. We control for an individual-specific vector of attributes X_i, which includes linear and quadratic terms for maternal age, child's sex, parity, urban or rural residence, number of multiple births, and birth day of the week. To control for shifts in seasonal patterns of birth that might be year-specific, we include conception year and month interaction fixed effects ζ_{ym}. Given these, Equation (1) compares the birth weights of infants conceived in the same calendar month and examines the associations of cumulative within-month variation in air pollution and temperature with variation of birth weights.

Equation (1) restricts the birth weight gradient with college education to be constant, which is captured by σ_0 and is invariant of ambient environmental exposures. Equation (2) relaxes this restriction, and allows the birth weight gradient with college education to potentially vary depending on P_i, Cold_i, and Heat_i:

$$\begin{aligned}
\text{Birthweight}_{\text{ymi}} = {} & \alpha + \zeta_{ym} + \sigma_0 \text{Edu}_i \\
& + \gamma_1 P_i + \gamma_2 \text{Cold}_i + \gamma_3 \text{Heat}_i \\
& + \sigma_1 \text{Edu}_i \times P_i + \sigma_2 \text{Edu}_i \times \text{Cold}_i + \sigma_3 \text{Edu}_i \times \text{Heat}_i \\
& + g\left(\text{Rainfall}_i\right) + \mathbf{X}_i \theta' + \varepsilon_i \,,
\end{aligned} \tag{2}$$

where positive values for σ_1, σ_2 and σ_3 combined with negative values for γ_1, γ_2 and γ_3 would imply protective effects of maternal college education that ameliorate the negative impacts of ambient air pollution, extreme cold and extreme heat on birth weight.

We estimate Equations (1) and (2) both via conditional mean (OLS) and conditional quantile estimation.[10] Under OLS, Equation (2) imposes the restriction that the birth weight-college education gradient—conditional on observed variables including the vector of environmental exposure measures P_i, Cold_i, and Heat_i—is constant across individuals. The implicit assumption is that while unobserved factors—including nutrition, avoidance behavior, genetic factors or other risk factors—can impact birth weight, there are no protective effects of maternal education that mediate these channels of unobserved underlying physical vulnerabilities. However, given the same ambient environment, the tendency for college-educated mothers to have babies with higher birth weight compared to non-college-educated mothers may be most pronounced at the lower conditional quantiles of unobserved underlying baby physical vulnerabilities. Additionally, babies with greater unobserved underlying physical vulnerabilities might be more likely to suffer from air pollution and extreme temperatures.

Our conditional quantile analysis allows birth weight-college education gradients to vary both along observed dimensions of sources of vulnerabilities, i.e., potential negative environmental factors (as seen in the interaction effects in Equation (2)), and along unobserved dimensions

10. Under OLS, the same estimated coefficients provide both conditional and unconditional mean predictions; under quantile estimations, conditional quantile estimates in general can differ from unconditional quantile results (Firpo, Fortin, and Lemieux 2009). In this paper, we use conditional quantile estimates to study heterogeneous maternal education and birth weight gradients on levels (grams) of birth weight. While Firpo, Fortin, and Lemieux (2009) show that in the context of birth weight, conditional and unconditional quantile estimates can be similar, we do not consider the implications of our estimates for the unconditional (marginal) distribution of birth weight. Also see Hao and Yeung's (2015) discussion for technical details of conditional quantile estimations. We estimate quantile regressions with the quantreg package (Koenker 2020).

of sources of baby vulnerabilities, as captured by different conditional quantiles. The results provide a finer disentangling of heterogeneities of the birth weight-maternal education gradients. For example, the conditional mean estimates could understate the importance of PM_{10} if the negative relationship between PM_{10} and birth weight is magnified at lower conditional quantiles where mothers/children have greater unobserved vulnerabilities.

4 Results

4.1 Mean Regression Results

Results from mean regressions with PM_{10} as the only air pollutant are presented in Table 3. Columns 1 and 3 show the results from Equation (1) estimations. Columns 2 and 4 show the results from Equation (2) estimations, which includes interaction terms between maternal education and environmental exposure variables. In columns 1 and 2, extreme temperature is defined by 1 percent extreme tails of past temperatures, while columns 3 and 4 use 2.5 percent as the tail cutoffs.

After controlling for conception year-by-month fixed effects, PM_{10}, extreme cold and extreme heat are all negatively and substantially associated with birth weight. Column 1 in Table 3 shows that a 1 µg/m3 increase in average daily PM_{10} potential exposure during pregnancy is associated with an 18.2 (s.e. 2.1) gram reduction of birth weight. An additional percentage point increase in potential exposure to extreme heat or cold is associated with a 47.2 (s.e. 11.4) or 39.3 (s.e. 16.2) gram birth weight reduction, respectively. Stated differently, a one standard deviation change in potential exposures to PM_{10} (i.e., 7.2 µg/m3), extreme heat (i.e., 1.09 percent of pregnant days), or extreme cold (i.e., 0.55 percent of pregnant days) correspond to 0.28, 0.11, and 0.05 standard deviation changes in birth weight, respectively.[11] The results from Columns 1 and 3 are similar. The exception is that in Column 3, with the less-extreme temperature thresholds, heat exposure is no longer negatively associated with birth weight.

11. While the magnitudes of the association between PM_{10} or other pollutants and birth weight in relatively low pollution settings is generally smaller than what we find here, our results are similar to the findings obtained by (Bharadwaj and Eberhard 2008) from Chile—a setting with similar mean PM_{10} exposures as our setting here—where they find that a one standard deviation (17 µg/m3) increase in PM_{10} exposures is associated with 0.23 standard deviations (125 grams) of birth weight reduction.

Columns 2 and 4 show the maternal college education interaction coefficient estimates.[12] In both columns, mothers' college education status is associated with reduced vulnerability to ambient air pollution and extreme heat exposures. However, this protective effect of college mothers is not significant for extreme cold. Focusing on Column 2, there is a positive college-education interaction coefficient of 2.0 (s.e. 0.6) for PM_{10} and 15.8 (s.e. 4.0) for extreme heat. Comparing college-educated to non-college-educated mothers, the interactions correspond to a 10 percent dampening of the negative association of PM_{10} with birth weight and a 29 percent dampening of the negative association of extreme heat with birth weight.

We evaluate the college premium in birth weight, which is the predicted gap in birth weight between college-educated and non-college-educated mothers, by considering the negative intercept for college education, -117.4 (s.e. 45.6), and the positive education slopes jointly. Holding extreme heat and cold exposures at their respective means, the college premium amounts to 0.05, 0.08, and 0.16 standard deviations of birth weight at the 1st (64 μg/m3), 50th (71 μg/m3) and 99th (91 μg/m3) percentiles of the marginal distribution of PM_{10}. Similarly, holding PM_{10} and extreme cold at their respective means, the college premium amounts to 0.05, 0.07 and 0.16 standard deviations of birth weight at the 1st (0 percent), 50th (0.73 percent) and 99th (3.16 percent) percentiles of the marginal distribution of percentage of pregnancy days exposed to extreme heat.

4.2 Quantile Regression Results

Conditional quantile results, without and with maternal education interactions with the three potential negative environmental measures, are shown in Tables 4 and 5 respectively. The estimations use the more stringent cold and heat exposure measures defined by the 1 percent cutoffs.

12. The coefficient for college education appears negative in interaction specifications (columns 2 and 4). In these specifications, college education coefficients represent intercepts (adjusting for other variables in the model) for the hypothetical situation of no PM10, cold, or heat exposure. The predicted protective effect of maternal education given the observed range of ambient environmental measures is presented in our college-premium of birthweight discussions.

4.2.1 Baseline Quantile Regression Results

Table 4 shows a negative gradient for college education over ascending conditional quantile estimates, indicating the protective effects of college education on birth weight decreases as we move from the left to the right tail of the conditional distribution of birth weight. Specifically, the coefficients on mother's college completion status are 77.2 (s.e. 8.2), 27.2 (s.e. 4.9), and 15.7 (s.e. 6.7) at the 10^{th}, 50^{th} and 90^{th} conditional quantiles. These amount to 0.16, 0.06 and 0.03 standard deviations of birth weight.

Additionally, the negative associations between the three environmental measures and birth weight are all stronger at lower conditional quantiles. The PM_{10} coefficients at the 10^{th}, 50^{th} and 90^{th} conditional quantiles are -31.9 (s.e. 3.7), -17.2 (s.e. 1.9), and -15.7 (s.e. 2.5). A one standard deviation increase in potential PM_{10} exposures is associated with 0.48, 0.26, and 0.24 standard deviation reductions of birth weight respectively. For extreme heat and cold, respectively, the magnitudes of the negative associations are 1.3 and 2.7 times larger at the 10^{th} conditional quantile versus the 90^{th}. At the 10^{th} conditional quantiles, a one standard deviation increase in extreme heat or cold is associated with a 0.08 or 0.10 standard deviation reduction of birth weights, respectively.[13]

Table 4 also indicates increasing estimates for males, decreasing estimates for mother's age, as well as increasing estimates for mother's age squared along ascending conditional quantiles estimates. The direction and magnitudes of these coefficients are similar to those reported in the existing research on conditional and unconditional quantile estimates for birth weight (Abrevaya 2001; Koenker and Hallock 2001; Firpo, Fortin, and Lemieux 2009).

4.2.2 Quantile Regression Results with Interactions

At lower conditional quantiles, maternal college education ameliorates the negative association between birth weight and pollution and extreme heat, but not extreme cold. As shown in Table 5 and Figure 3, the college-education interaction coefficient estimates for PM_{10} are 3.9 (s.e.

13. We note that Column 1 of Table 3 and Table 4 show that the mean point estimate for PM_{10} and extreme cold exposures are both between the point estimates for the 10^{th} and the 90^{th} conditional quantiles. The point estimate for extreme heat, however, is out of the range of the conditional quantile estimates for extreme heat. This indicates that the OLS result for extreme heat might be driven by data from the extreme left tail of the conditional distribution.

1.1), 0.7 (s.e. 0.6), and 0.7 (s.e. 1.1) at the 10th, 50th, and 90th conditional quantiles. These respectively correspond to a 11, 4, and 4 percent reduction in the substantial negative associations between PM_{10} and birth weight compared to non-college-educated mothers. Additionally, the college-education interaction coefficient estimates for extreme heat are 32.3 (s.e. 7.5), 8.8 (s.e. 4.4), and 8.6 (s.e. 6.5) at the 10th, 50th, and 90th conditional quantiles. While the overall associations of extreme heat with birth weight are less substantial than the associations of PM_{10} with birthweight, these coefficients, respectively, correspond to a 64, 29, and 29 percent reduction in the associations between extreme heat and birth weight.

Considering jointly the positive slopes and negative intercepts from Table 5, the college premium in birth weight is magnified at lower conditional quantiles. Holding heat and cold exposure variables at their means, the college premiums at the 1st, 50th and 99th percentiles of the marginal distribution of PM_{10} amount to 0.02, 0.03, and 0.06 standard deviations of birth weight with 90th conditional quantile estimates, and are magnified five times to 0.09, 0.15, and 0.31 standard deviations of birth weight with 10th conditional quantile estimates. These results are visualized in Figure 4. Additionally, holding PM_{10} and cold exposures at their means, the college premiums at the 1st, 50th and 99th percentiles of the marginal distribution of extreme heat amount to 0.01, 0.02, and 0.07 standard deviations of birth weight with the 90th conditional quantile estimates, and are magnified to 0.08, 0.13, and 0.30 standard deviations with the 10th conditional quantile estimates. Notably, the association between extreme cold exposures and birth weight does not vary across maternal education group, so there are no significant variations in the college premium in birth weight as extreme cold exposures increase.

4.3 Composite Index Analysis

We repeat the analyses for PM_{10} with the composite index pollution measure. Detailed results are presented in Appendix Tables A1, A2 and A3. Patterns in the temperature results are robust to choice of pollution measure, and will not be discussed here. The results from the composite index analysis closely mirror the patterns revealed in the PM_{10} analysis. There is a protective effect of maternal education with regard to pollution, and the finding persists across conditional quantiles of birth weight. Further, quantile regressions show that the negative associations between pollution and birth weight, and the protective effects of maternal education with respect to pollution, are magnified at lower conditional quantiles.

A key difference in the composite index analysis results is that for estimations based on Equation (1) without maternal education interactions, the birth weight change associated with one standard deviation change in the composite index is 1.8 times of the corresponding change in the PM_{10} analysis. In the regressions with interactions, the protective effect of college education is weaker in the composite index analysis than in the PM_{10} analysis. Together, these factors lead to a pattern in which the college premium in grams of birth weight along the marginal distribution of the composite index is approximately the same as the college premium in birth weight along the marginal distribution of PM_{10}.

5 Summary and Conclusions

In this paper, we link a database of all births recorded for three years born in hospitals in a district in Guangzhou, China to daily measures of particulate matter (PM_{10}), nitrogen dioxide, and sulfur dioxide and to daily meteorological measurements during pregnancies. Using conditional mean and quantile regressions, we estimate the associations of birth weight with air pollution, measured by ambient PM_{10} and a composite pollution measure, and with extreme cold and hot temperatures. Our paper adds to a small number of studies that consider effect modifications of pollution and extreme weather by maternal education. To our knowledge, it is the one of the first to address whether the protective effects of maternal education are heterogeneous with respect to unobserved, underlying physical vulnerabilities.

We find a strong negative association between ambient PM_{10} and extreme temperature exposures and birth weight. For example, a one standard deviation increase in PM_{10} exposure—7.2 μg/m3—is associated with a 92 to 229 gram reduction in birth weight. A one standard deviation—on average 1.5 days—increase in prenatal exposure to extreme cold temperatures (lower than -2.42 degrees Celsius in universal thermal climate indices) is associated with a 15 to 48 gram reduction in birth weight. A one standard deviation—on average 3.0 days—increase in prenatal exposure to extreme hot temperatures (higher than 34.47 degrees Celsius, in universal thermal climate indices) is associated with a 26 to 51 gram reduction in birth weight. Stronger associations are seen for children with greater levels of underlying physical vulnerabilities at lower conditional quantiles.

There is also strong evidence for effect modification with maternal education. Mothers with college degrees experience an amelioration of effects on birth weight of PM_{10} by about 4 to 11 percent, and of extreme hot weather by 29 to 62 percent, with larger buffering effects experienced by those at lower conditional quantiles. However, there is no effect modification with maternal education in response to extreme cold weather. This result is understandable in a context in which heating service is not available. Although there is usually only a short spell of very cold weather in each year, our results indicate that even a few days of very cold weather exposure is associated with lower birth weight. Given lack of heating indoors, even mothers with higher socioeconomic status might have no effective way of protecting themselves from exposure to extreme cold weather. On the contrary, air conditioning was widely available during the time period of this study and was very accessible for higher socioeconomic status mothers.

In short, our findings demonstrate that babies of college-educated mothers—compared to babies of other mothers in the same district of Guangzhou—experienced a reduction of risk in the context of air pollution and extreme heat exposure. It is important to note that the benefits accruing to babies of college-educated mothers vary. The protective effects are most pronounced among those experiencing more environmental risk—more extreme ambient pollution and heat exposure. Protective effects of maternal education also emerge more strongly among mothers of infants with greater unobserved underlying physical vulnerabilities. From a different perspective, socioeconomic disparities and underlying child health vulnerabilities stratify the realized impacts associated with a common ambient environment—especially when that common ambient environment is extremely polluted or extremely hot. Our findings suggest that babies at greatest risk from high pollution levels and increasingly frequent heat events are those at the nexus of socioeconomic and physical vulnerability.

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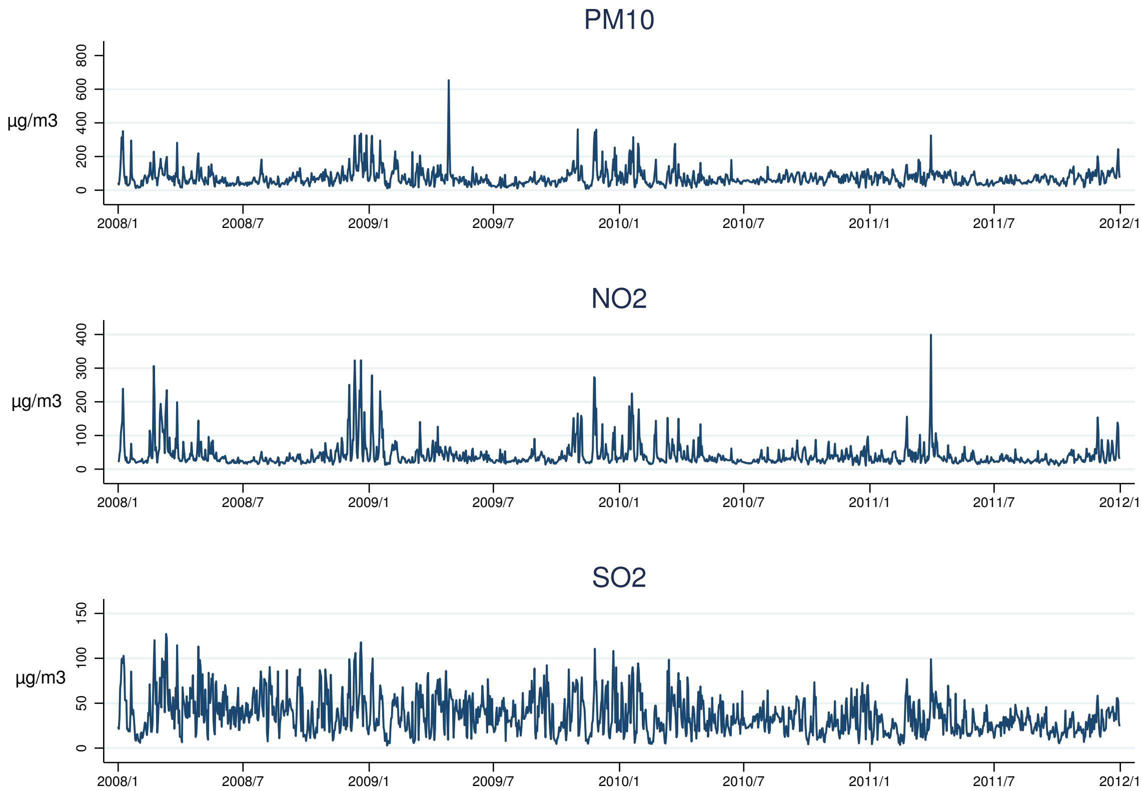
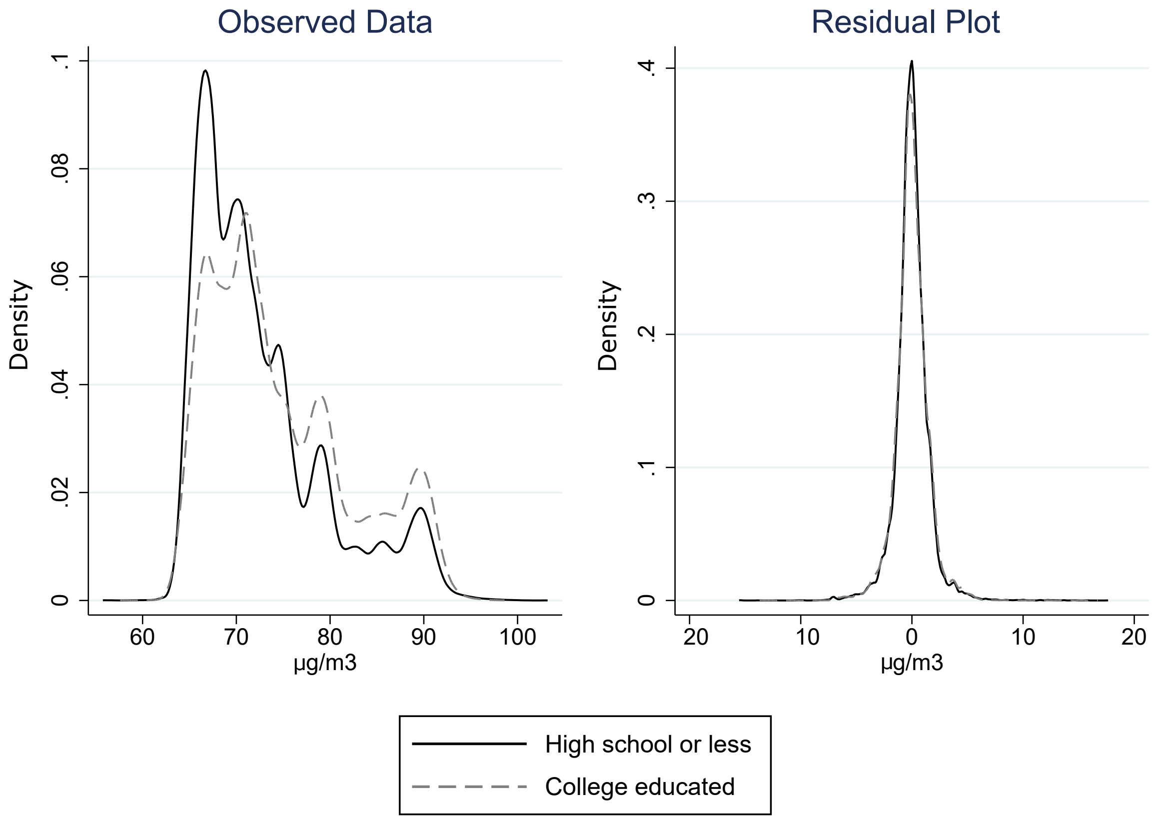
Fig. 1. Daily mean ambient air pollution levels by three major pollutants, 2008 to 2011, Guangzhou, China.



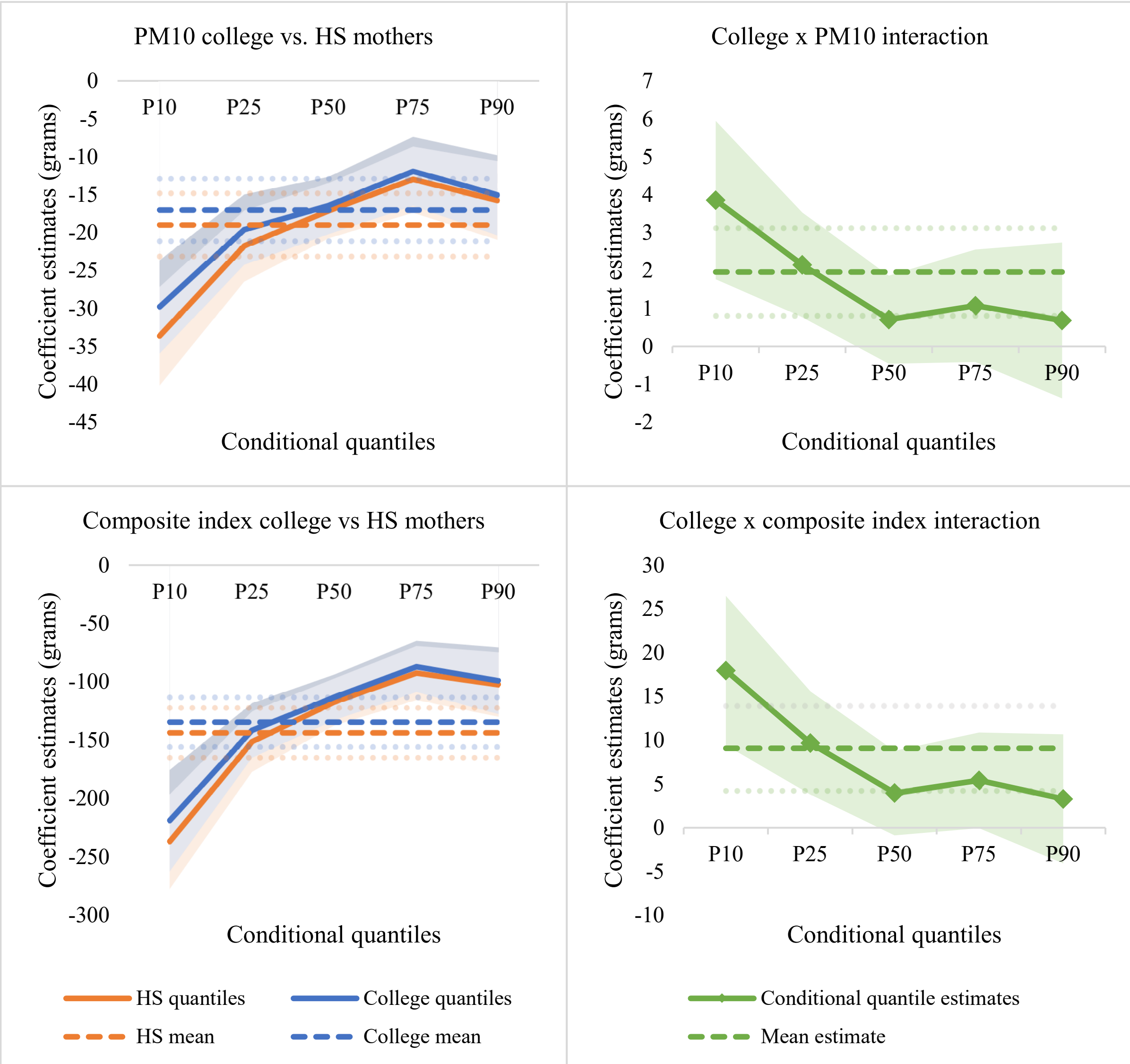
Notes: This figure shows daily means for three monitored ambient air pollutants in Guangzhou between 2008 and 2011.

Fig. 2. Daily mean ambient PM_{10} exposure by mother's education.



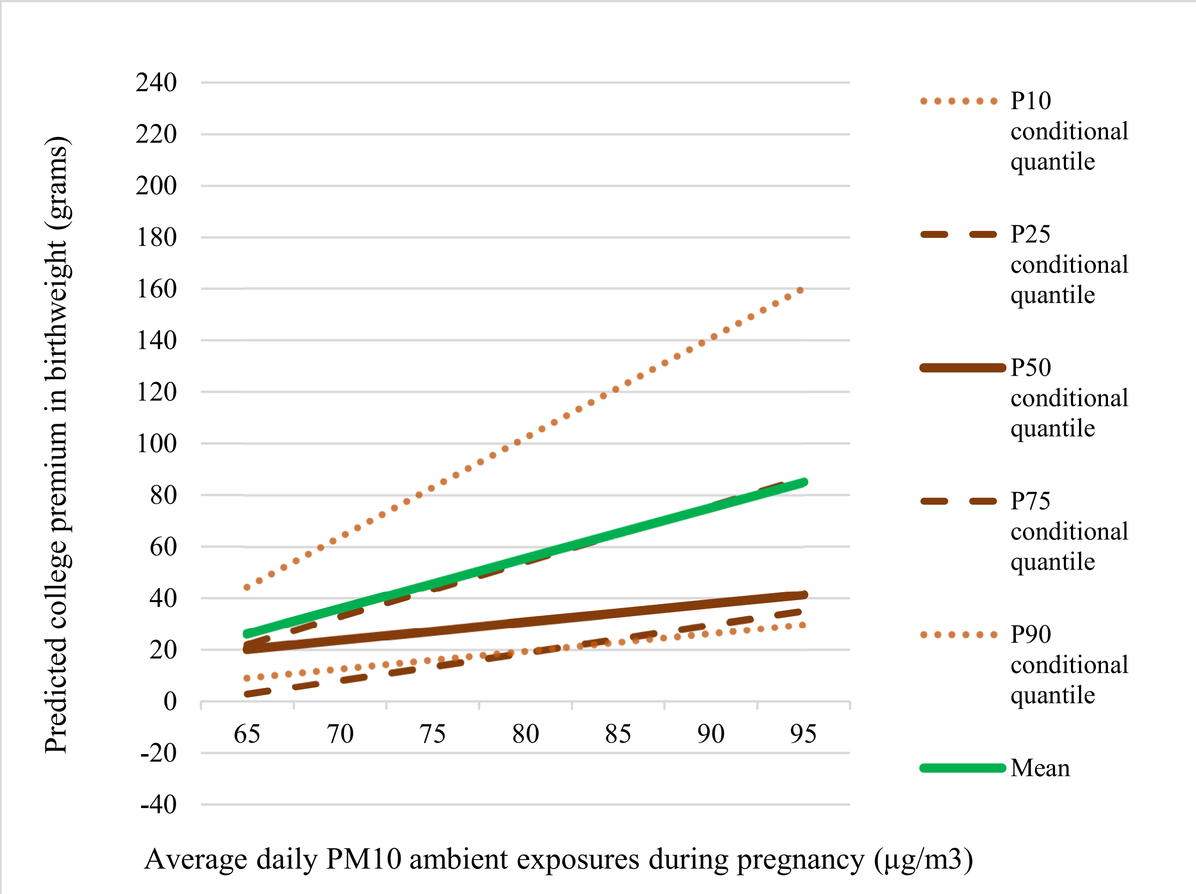
Notes: The left panel contains observed data, while the right panel depicts the conditional distribution of daily mean ambient PM_{10} exposure after controlling for conception year and month interaction fixed effects.

Fig. 3. Graphical illustration of mean and conditional quantile estimation coefficients from models of birth weight (grams) for average daily mean ambient PM_{10} exposures (μg/m3) (top row) and composite index (bottom row) for mothers with college education and mothers with high school or less education (HS).



Notes: The x-axis of the sub-plots correspond to results from different conditional quantile estimations. We interpret lower conditional quantiles as corresponding to higher levels of unobserved underlying physical vulnerabilities for babies. The two subfigures on the top row are based on estimates from Tables 3 and 5. The two subfigures on the bottom row are based on estimates from Appendix Tables A1 and A3. The y-axis reports regression coefficients. For the top row, coefficients indicate grams of birth weight change for each additional μg/m3 of average daily mean ambient PM_{10} exposures. For the bottom row, coefficients indicate grams of birth weight change for each additional index unit of the composite index.

Fig. 4. Graphical illustration of predicted college premium in birth weight for different conditional quantiles and at different ambient PM_{10} exposure levels.



Notes: The x-axis of the figure represents different ambient PM_{10} exposure levels during the course of pregnancy, which correspond to the range of ambient PM_{10} exposure levels reported in Table 2. The y-axis reports predicted college premium in birth weight–the predicted gap in birth weight between college-educated and non-college-educated mothers. Given estimates from Tables 3 and 5, each line corresponds to predictions for children at differing conditional quantiles. The premium is greater at higher ambient exposure levels and for children with higher levels of underlying vulnerabilities–those at lower conditional quantiles.

Table 1: Summary statistics.

	All		Comparison by mother's education				
			<=high school		>=college		gap[‡]
	mean	s.d.	mean	s.d.	mean	s.d.	p-value
Child variables							
Sex (male=1)	0.53	0.50	0.54	0.50	0.53	0.50	(0.01)
Birth weight (grams)	3181	473	3166	492	3213	430	(0.00)
Maternal variables							
Mother's age (years)	29.06	4.19	28.81	4.52	29.56	3.36	(0.00)
Mother's schooling attainment (years)	13.08	2.25	11.69	1.05	15.89	1.15	(0.00)
Parity	1.25	0.52	1.34	0.58	1.06	0.26	(0.00)
Locality (urban =1)	0.98	0.13	0.98	0.15	0.99	0.08	(0.00)
Average of daily mean ambient pollution exposures during pregnancy							
PM_{10} (μg/m3)	73.25	7.17	72.57	6.91	74.63	7.49	(0.00)
NO_2 (μg/m3)	41.43	6.13	40.66	6.02	43.01	6.07	(0.00)
SO_2 (μg/m3)	35.21	4.63	34.51	4.65	36.62	4.26	(0.00)
Composite index of PM_{10}, NO_2, SO_2	-0.04	1.56	-0.24	1.53	0.38	1.53	(0.00)
Temperature and rainfall during pregnancy							
Average daily rainfall (mm)	5.14	1.61	5.20	1.63	5.03	1.55	(0.00)
Average daily mean temperature (C°)	22.38	1.83	22.33	1.86	22.50	1.77	(0.00)
Percent of pregnancy days with ambient exposure to extreme temperatures							
Extreme heat, above past 99%	1.19	1.09	1.11	1.04	1.34	1.16	(0.00)
Extreme cold, below past 1%	0.89	0.55	0.88	0.53	0.91	0.58	(0.00)
Extreme heat, above past 97.5%	2.79	2.10	2.67	2.01	3.04	2.24	(0.00)
Extreme cold, below past 2.5%	2.44	1.36	2.52	1.38	2.30	1.30	(0.00)

The analytic sample has 54,828 observations. Sources and computations for ambient environmental variables are discussed in the data section of the paper.
[‡] P-value from testing whether the mean gap for each variable between college-educated and non-college-educated mothers is statistically different.

Table 2: Distribution of cumulative local ambient PM_{10}, composite index and extreme temperature exposures during the course of pregnancy.

Statistics	Pollution measures		Varying cutoffs for extreme temperature exposures			
			1 percent cutoff		2.5 percent cutoff	
	PM_{10} μg/m3	composite index	heat percent days	cold percent days	heat percent days	cold percent days
Percentiles						
P1	64.32	-2.27	0.00	0.00	0.00	0.00
P5	65.22	-2.12	0.00	0.00	0.00	0.36
P10	65.88	-1.81	0.00	0.35	0.36	0.71
P25	67.55	-1.47	0.70	0.37	1.43	1.41
P50	71.32	-0.35	0.73	1.05	1.87	2.56
P75	77.04	1.18	2.54	1.12	4.78	3.76
P90	85.40	2.47	2.93	1.79	6.20	4.03
P95	89.23	2.85	3.00	1.85	6.34	4.12
P99	91.35	3.13	3.16	1.93	6.67	4.37
Min and Max						
Min	55.77	-2.39	0.00	0.00	0.00	0.00
Max	103.21	4.46	4.23	2.79	8.99	5.98

Note: Figures reported in the table represent distributional statistics along the marginal distribution of ambient pollution and extreme temperature variables.

Table 3: OLS regression analysis of birth weight with interactions of ambient PM_{10} and extreme temperature with maternal education.

	Varying cutoffs of extreme temperature exposures			
	1 percent cutoff		2.5 percent cutoff	
Variable	(1)	(2)	(3)	(4)
Environmental exposure variables				
PM_{10}	-18.23**	-18.98**	-15.32**	-16.06**
	(2.10)	(2.12)	(2.18)	(2.21)
Extreme heat	-47.19**	-53.51**	0.55	-2.26
	(11.43)	(11.65)	(7.19)	(7.32)
Extreme cold	-39.28*	-38.41*	-30.72**	-30.59**
	(16.20)	(16.49)	(7.13)	(7.24)
Education and environmental exposure interactions				
College educated	45.02**	-117.40*	45.16**	-129.20*
	(4.41)	(45.64)	(4.41)	(50.26)
College x PM_{10}		1.96**		2.07**
		(0.59)		(0.61)
College x extreme heat		15.75**		7.99**
		(3.95)		(2.31)
Ccollege x extreme cold		-2.99		-0.83
		(7.53)		(3.54)
Control variables				
Male	104.30**	104.30**	104.10**	104.10**
	(3.90)	(3.90)	(3.90)	(3.90)
Mother's age	54.99**	54.53**	55.06**	54.59**
	(4.89)	(4.89)	(4.89)	(4.89)
Mother's age^2	-0.89**	-0.88**	-0.89**	-0.88**
	(0.08)	(0.08)	(0.08)	(0.08)
Intercept	1132.00**	1203.00**	970.30**	1043.00**
	(207.90)	(209.30)	(213.40)	(215.10)
Observations	54,828	54,828	54,828	54,828
R^2	0.070	0.071	0.070	0.071

Notes: Regressions control for urban residence status, conception year and month interaction fixed effects, day of the week at birth, parity and daily mean rainfall.
† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. Bootstrap standard errors are shown in parentheses.

Table 4: Conditional quantile regression analysis of birth weight with ambient PM_{10} and extreme temperature and maternal education.

	Estimates at conditional quantiles				
Variable	P10	P25	P50	P75	P90
Environmental exposure variables					
PM_{10} ^{a,b,c}	-31.91**	-20.73**	-17.18**	-12.88**	-15.70**
	(3.68)	(2.17)	(1.93)	(2.17)	(2.49)
Extreme heat	-32.941	-25.068*	-29.74**	-23.54†	-25.90†
	(21.03)	(11.89)	(10.79)	(12.61)	(15.65)
Extreme cold ^{a}	-86.33**	-33.29†	-31.34*	-27.39†	-32.19
	(26.34)	(17.48)	(14.99)	(15.93)	(22.82)
Education					
College educated ^{a,b,c,d}	77.18**	41.17**	27.23**	13.64*	15.69*
	(8.18)	(5.17)	(4.87)	(5.31)	(6.70)
Control variables					
Male	84.54**	92.59**	108.60**	115.89**	132.34**
	(6.74)	(4.64)	(4.61)	(4.94)	(6.30)
Mother's age	70.04**	49.20**	47.23**	51.99**	41.09**
	(9.92)	(5.41)	(4.99)	(5.39)	(8.34)
Mother's age^2	-1.18**	-0.79**	-0.75**	-0.80**	-0.60**
	(0.17)	(0.09)	(0.08)	(0.09)	(0.14)
Intercept	941.49**	1323.99**	1885.75**	1920.80**	2528.82**
	(343.00)	(260.62)	(235.01)	(244.45)	(311.43)
Observations	54,828	54,828	54,828	54,828	54,828

Notes: Regressions control for urban residence status, conception year and month interaction fixed effects, day of the week at birth, parity and daily mean rainfall.
Given bootstraped simultaneous conditional quantile estimates, superscripts a, b, c and d indicate whether estimates across conditional quantiles are statistically different for the three ambient envirnment or education variables.
[a] P10, P25 and P50 are significantly different at 0.05 sig. level.
[b] P10 and P90 are significantly different at 0.05 sig. level.
[c] P25 and P75 are significantly different at 0.05 sig. level.
[d] P50, P75 and P90 are significantly different at 0.05 sig. level.
† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. Bootstrap standard errors are shown in parentheses.

Table 5: Conditional quantile regression analysis of birth weight with interactions of ambient PM_{10} and extreme temperature with maternal education.

	Estimates at conditional quantiles				
Variable	P10	P25	P50	P75	P90
Environmental exposure variables					
PM_{10} ^{a,b,c}	-33.63**	-21.76**	-17.12**	-12.97**	-15.75**
	(3.31)	(2.40)	(1.86)	(2.22)	(2.66)
Extreme heat	-50.20*	-32.29*	-30.16**	-28.48*	-30.27†
	(21.32)	(13.68)	(10.89)	(12.19)	(16.26)
Extreme cold ^{a}	-86.33**	-35.63*	-26.08†	-22.55	-31.81
	(24.79)	(16.50)	(14.63)	(16.00)	(24.76)
Education and environmental exposure interactions					
College educated ^{a,b}	-252.72**	-133.76*	-26.32	-70.73	-39.21
	(80.04)	(54.35)	(47.23)	(58.47)	(80.66)
College x PM_{10} ^{a,b}	3.86**	2.15**	0.70	1.07	0.68
	(1.06)	(0.70)	(0.59)	(0.76)	(1.05)
College x extreme heat ^{a,b}	32.28**	11.53*	8.82*	9.64†	8.64
	(7.47)	(5.27)	(4.44)	(5.08)	(6.52)
College x extreme cold	9.13	2.40	-10.92	-8.46	-7.02
	(14.25)	(8.03)	(8.82)	(8.39)	(11.38)
Control variables					
Male	84.51**	91.76**	107.95**	115.88**	133.56**
	(7.80)	(4.85)	(4.11)	(5.04)	(6.96)
Mother's age	68.18**	47.92**	47.13**	51.37**	41.76**
	(8.99)	(5.37)	(5.00)	(5.10)	(8.64)
Mother's age^2	-1.15**	-0.77**	-0.74**	-0.79**	-0.61**
	(0.15)	(0.09)	(0.08)	(0.08)	(0.15)
Intercept	1180.91**	1434.43**	1891.26**	1923.30**	2460.86**
	(327.27)	(253.20)	(239.58)	(244.98)	(333.48)
Observations	54,828	54,828	54,828	54,828	54,828

Notes: Regressions control for urban residence status, conception year and month interaction fixed effects, day of the week at birth, parity and daily mean rainfall.
Given bootstraped simultaneous conditional quantile estimates, superscripts a, b, c and d indicate whether estimates across conditional quantiles are statistically different for the three ambient envirnment or education variables.
[a] P10, P25 and P50 are significantly different at 0.05 sig. level.
[b] P10 and P90 are significantly different at 0.05 sig. level.
[c] P25 and P75 are significantly different at 0.05 sig. level.
[d] P50, P75 and P90 are significantly different at 0.05 sig. level.
† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. Bootstrap standard errors are shown in parentheses.

A Additional Tables (For Online Publication)

In this Appendix section, we repeat the analyses for PM_{10} with the composite index pollution measure. Results are presented in Appendix Tables A1, A2 and A3. Patterns in the temperature results are robust to choice of pollution measure. The results from the composite index analysis closely mirror the patterns revealed in the PM_{10} analysis. There is a protective effect of maternal education with regard to pollution, and the finding persists across conditional quantiles of birth weight (see the dotted lines in Figure 3 Bottom Row). Further, quantile regressions show that the negative associations between the pollution and birth weight, and the protective effects of maternal education with respect to pollution, are magnified at lower conditional quantiles (see the solid lines and shaded areas in Figure 3 Bottom Row). See Section 4.3 for more discussion.

Table A1: OLS regression analysis of birth weight with interactions of ambient composite index and extreme temperature with maternal education.

	Varying cutoffs of extreme temperature exposures			
	1 percent cutoff		2.5 percent cutoff	
Variable	(1)	(2)	(3)	(4)
Environmental exposure variables				
Composite index	-139.90**	-143.50**	-129.50**	-132.90**
	(10.81)	(10.87)	(11.03)	(11.08)
Extreme heat	-51.80**	-56.69**	-5.41	-7.51
	(11.52)	(11.74)	(7.07)	(7.19)
Extreme cold	-26.81†	-25.05	-29.52**	-29.31**
	(16.14)	(16.44)	(7.11)	(7.22)
Education and environmental exposure interactions				
College educated	45.01**	32.36**	45.17**	27.27*
	(4.40)	(9.46)	(4.40)	(12.92)
College x composite index		9.08**		9.25**
		(2.48)		(2.49)
College x extreme heat		12.14**		6.08**
		(3.89)		(2.19)
Ccollege x extreme cold		-5.88		-1.03
		(7.52)		(3.53)
Control variables				
Male	104.60**	104.60**	104.40**	104.40**
	(3.89)	(3.89)	(3.89)	(3.89)
Mother's age	54.68**	54.16**	54.75**	54.23**
	(4.88)	(4.88)	(4.88)	(4.89)
Mother's age^2	-0.88**	-0.87**	-0.88**	-0.87**
	(0.08)	(0.08)	(0.08)	(0.08)
Intercept	-346.20**	-331.40*	-262.00†	-244.10†
	(134.20)	(134.30)	(134.70)	(134.90)
Observations	54,828	54,828	54,828	54,828
R^2	0.073	0.073	0.073	0.073

Notes: Regressions control for urban residence status, conception year and month interaction fixed effects, day of the week at birth, parity and daily mean rainfall.
† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. Bootstrap standard errors are shown in parentheses.

Table A2: Conditional quantile regression analysis of birth weight with ambient composite index and extreme temperature and maternal education.

	Estimates at conditional quantiles				
Variable	P10	P25	P50	P75	P90
Environmental exposure variables					
Composite index ^{a,b,c,d}	-233.07**	-147.23**	-113.18**	-89.70**	-102.53**
	(21.22)	(12.78)	(10.64)	(11.58)	(13.16)
Extreme heat	-42.95†	-25.64*	-26.16**	-25.42*	-23.84
	(22.44)	(11.51)	(10.07)	(11.38)	(15.22)
Extreme cold	-55.90*	-20.30	-18.08	-24.87	-27.23
	(25.94)	(17.60)	(14.29)	(15.95)	(24.78)
Education					
College educated ^{a,b,c,d}	76.86**	40.99**	28.41**	14.26*	15.65*
	(8.65)	(5.76)	(4.79)	(6.02)	(7.35)
Control variables					
Male	85.50**	91.24**	108.97**	116.63**	131.41**
	(6.89)	(5.08)	(4.17)	(5.03)	(6.32)
Mother's age	68.58**	49.11**	47.50**	52.67**	41.72**
	(10.03)	(5.47)	(4.49)	(5.32)	(8.82)
Mother's age^2	-1.16**	-0.79**	-0.75**	-0.81**	-0.61**
	(0.17)	(0.09)	(0.07)	(0.09)	(0.15)
Intercept	-1280.41**	-151.86	584.87**	956.19**	1260.17**
	(199.56)	(163.02)	(174.74)	(177.41)	(257.64)
Observations	54,828	54,828	54,828	54,828	54,828

Notes: Regressions control for urban residence status, conception year and month interaction fixed effects, day of the week at birth, parity and daily mean rainfall.
Given bootstraped simultaneous conditional quantile estimates, superscripts a, b, c and d indicate whether estimates across conditional quantiles are statistically different for the three ambient envirnment or education variables.
[a] P10, P25 and P50 are significantly different at 0.05 sig. level.
[b] P10 and P90 are significantly different at 0.05 sig. level.
[c] P25 and P75 are significantly different at 0.05 sig. level.
[d] P50, P75 and P90 are significantly different at 0.05 sig. level.
† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. Bootstrap standard errors are shown in parentheses.

Table A3: Conditional quantile regression analysis of birth weight with interactions of ambient composite index and extreme temperature with maternal education.

	Estimates at conditional quantiles				
Variable	P10	P25	P50	P75	P90
Environmental exposure variables					
Composite index ^{a,b,c}	-236.66**	-151.13**	-117.05**	-92.11**	-102.06**
	(20.61)	(13.21)	(10.35)	(11.82)	(14.19)
Extreme heat	-58.51**	-30.01*	-29.58**	-27.86*	-29.70†
	(20.63)	(11.80)	(11.16)	(12.55)	(17.83)
Extreme cold	-59.40*	-22.27	-14.05	-20.31	-22.39
	(28.42)	(18.03)	(15.95)	(15.58)	(23.22)
Education and environmental exposure interactions					
College educated	46.94*	30.78**	27.25**	14.10	11.97
	(19.19)	(11.35)	(10.58)	(11.81)	(16.06)
College x composite index ^{a,b}	17.96**	9.69**	3.96	5.42†	3.30
	(4.35)	(3.01)	(2.47)	(2.79)	(3.76)
College x extreme heat ^{a}	26.86**	7.43	7.59†	7.43	9.18
	(8.18)	(4.71)	(4.50)	(4.64)	(6.80)
Ccollege x extreme cold	-3.15	-1.57	-11.45	-10.50	-9.01
	(14.46)	(8.38)	(8.24)	(8.67)	(12.42)
Control variables					
Male	85.88**	91.55**	107.52**	116.58**	132.41**
	(7.53)	(4.41)	(3.95)	(4.62)	(6.42)
Mother's age	63.94**	49.08**	47.70**	52.42**	42.82**
	(9.92)	(5.57)	(4.91)	(5.42)	(8.73)
Mother's age^2	-1.08**	-0.79**	-0.75**	-0.81**	-0.63**
	(0.17)	(0.09)	(0.08)	(0.09)	(0.15)
Intercept	-1134.55**	-152.53	628.65**	973.38**	1243.99**
	(175.64)	(183.35)	(185.93)	(183.07)	(253.32)
Observations	54,828	54,828	54,828	54,828	54,828

Notes: Regressions control for urban residence status, conception year and month interaction fixed effects, day of the week at birth, parity and daily mean rainfall.
Given bootstraped simultaneous conditional quantile estimates, superscripts a, b, c and d indicate whether estimates across conditional quantiles are statistically different for the three ambient envirnment or education variables.
[a] P10, P25 and P50 are significantly different at 0.05 sig. level.
[b] P10 and P90 are significantly different at 0.05 sig. level.
[c] P25 and P75 are significantly different at 0.05 sig. level.
[d] P50, P75 and P90 are significantly different at 0.05 sig. level.
† $p < 0.10$; * $p < 0.05$; ** $p < 0.01$. Bootstrap standard errors are shown in parentheses.

B Acquiring Environmental Data (For Online Publication)

A wide array of environmental data is available at detailed geographical units across the globe from the the European Centre for Medium-Range Weather Forecasts (ECMWF) at the Copernicus Climate Change Service. Copernicus provides data access via a free and publicly accessible API service. In this appendix section, we describe how we obtained key environmental data used in this paper using Copernicus.

B.1 Data Retrieval

Copernicus offers a range of data in different formats with similar data request structures. In particular, temperature as well as other environmental data based on observations from across the globe (with reanalysis) are available from the ERA5 Pressure Level as well as the ERA5 Single Level datasets.

B.1.1 Single Data Retrieval Request

To acquire Chinese data for the particular period in which our birth outcome data are available, we need to specify the appropriate time ranges as well as the geographical coordinates. We retrieve hourly data from every day between the year 2007 and 2012 by specifying the appropriate *year*, *month*, *day*, and *time* parameters. We specify our data acquisition geographical area as to the south-east of latitude and longitude coordinates (in decimal degrees) $(23.50, 113.00)$ and to the north-west of coordinates $(22.25, 114.50)$, which covers the broad geographical area that is relevant for our paper. Our specification for the *area* parameter is therefore $[23.50, 113.00, 22.25, 114.5]$.

Given this information and after registering with Copernicus to obtain an user-specific url and passkey, Source Code 1 provides a API call to acquire temperature data from Copernicus in *grib* format.

Source Code 1: Single Data Retrieval Call

```
# Library
import cdsapi
import urllib.request

# download folder
spt_root = "C:/data/"
spn_dl_test_grib = spt_root + "test_china_temp.grib"
# request
c = cdsapi.Client()
res = c.retrieve("reanalysis-era5-pressure-levels",
         {
             'product_type': 'reanalysis',
             'variable': 'temperature',
             'pressure_level': '1000',
             'year': [ '2007', '2008','2009', '2010', '2011', '2012' ]
             'month': [ '01','02','03','04','05','06', '07','08','09','10','11','12'],
             'day': [
                '01','02','03','04','05','06','07','08','09','10','11','12',
                '13','14','15','16','17','18','19','20','21','22','23','24',
                '25','26','27','28','29','30','31'
             ],
             'time': [
                '00:00', '01:00', '02:00', '03:00', '04:00', '05:00', '06:00', '07:00', '08:00',
                '09:00', '10:00', '11:00', '12:00', '13:00', '14:00', '15:00', '16:00', '17:00',
                '18:00', '19:00', '20:00', '21:00', '22:00', '23:00'
             ],
             'area': [23.50, 113.00, 22.25, 114.5],
             'grid': [1.25, 0.25],
             "format": "grib"
         },
         spn_dl_test_grib
         )
```

B.1.2 Subdivided Data Retrieval Request

A challenge to taking full advantage of the data is that, given the fine geographical and time units, the resulting data files can become very large. A single call to acquire all relevant data as shown in the example above can only be implemented on a server with access to Terabytes of storage space.

To deal with this challenge, we divide our API calls into smaller components. We make multiple requests of data at shorter time intervals. Each time we aggregate and process the relevant data before downloading the next set of data. Given the computational resources at our disposal, we download the data at six months intervals, as shown in Source Code 2. Given the computing resources available to the researcher, the time intervals can be further shortened to circumvent computational challenges from using the data.

Source Code 2: Sub-Period Data Retrieval Call

```
# date lists
ar_years = 2001:2019
ar_months_g1 = ['01','02','03','04','05','06']
ar_months_g2 = ['07','08','09','10','11','12']

# Loop over time periods
for it_yr in ar_years:
    for it_mth_group in [1, 2]:
        if it_mth_group == 1:
            ar_months = ar_months_g1
        if it_mth_group == 2:
            ar_months = ar_months_g2

        c = cdsapi.Client()
        res = c.retrieve(
            'reanalysis-era5-pressure-levels',
            {
                'product_type': 'reanalysis',
                'variable': 'temperature',
                'pressure_level': '1000',
                'year': [it_yr],
                'month': ar_months,
                 'day': [
                    '01','02','03','04','05','06','07','08','09','10','11','12',
                    '13','14','15','16','17','18','19','20','21','22','23','24',
                    '25','26','27','28','29','30','31'
                 ],
                'time': [
                    '00:00', '01:00', '02:00', '03:00', '04:00', '05:00', '06:00', '07:00', '08:00',
                    '09:00', '10:00', '11:00', '12:00', '13:00', '14:00', '15:00', '16:00', '17:00',
                    '18:00', '19:00', '20:00', '21:00', '22:00', '23:00'
                ],
                'area': [23.50, 113.00, 22.25, 114.5],
                'grid': [0.25, 0.25],
                'format': 'grib'
            },
            "china_temp.grib")
```

B.2 Data Processing

The data we download is at finer detail than required by the statistical analysis. For each sub-period of data downloaded, we process the data using a variety of tools. Data in the *grib* format is processed using the xarray package as shown in Source Code 3. Data in *netCDF* format is processed using the netCDF4 package as shown in Source Code 4. We store the resulting aggregate data as csv files and combine that with the rest of our child birth outcome data to conduct relevant statistical analysis.

Source Code 3: Grib Data Processing with xarray

```python
# Load Packages
import pandas as pd
import xarray as xr

# Process grid data
snm_data_grib, snm_data_csv = "data.grib", "data.csv"
dsxr = xr.load_dataset(snm_data_grib, engine='cfgrib')
pd.concat([dsxr['u10'].to_series(), dsxr['v10'].to_series(),
           dsxr['d2m'].to_series(), dsxr['t2m'].to_series(),
           dsxr['msl'].to_series(), dsxr['sp'].to_series()],
          axis=1).to_csv(snm_data_csv, index=True)
```

Source Code 4: netcdf Data Processing with netCDF4

```python
# Load Packages
import pandas as pd
from netCDF4 import Dataset, date2num, num2date

# Process netCDF data
snm_data_nc, snm_data_csv = "data.nc", "data.csv"
ds_src = Dataset(snm_data_nc)
var_tp = ds_src.variables['tp']

# Get the three dimensions, time, lat, and long
time_dim, lat_dim, lon_dim = var_tp.get_dims()
time_var = ds_src.variables[time_dim.name]
times = num2date(time_var[:], time_var.units)

# The flattening at the end converts variables to single column
latitudes = ds_src.variables[lat_dim.name][:]
longitudes = ds_src.variables[lon_dim.name][:]

# Convert to dataframe
[mt_times, mt_lat, mt_long] = np.meshgrid(times, latitudes, longitudes, indexing='ij')
ar_times = np.ravel(mt_times)
ar_lat = np.ravel(mt_lat)
ar_long = np.ravel(mt_long)
df = pd.DataFrame({'time': [t.isoformat() for t in ar_times],
                   'latitude': ar_lat, 'longitude': ar_long, 'tp': var_tp[:].flatten()})

# Get date and hour
df['date'] = pd.to_datetime(df['time']).dt.date
df['hour'] = pd.to_datetime(df['time']).dt.hour

# sort and group, and summ
sr_day_sum = df.groupby(['latitude','longitude','date'])['tp'].sum()
df_day_sum = sr_day_sum.reset_index()

# convert to csv
df_day_sum.to_csv(snm_data_csv, index=False)
```