Early exposure to air pollution and cognitive development later in life: Evidence from China

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Abstract

This paper studies the relationship between prenatal exposure to air pollution and youth cognitive skill development in China in 2008. This study combines the air pollution data by location compiled by the World Bank with the Chinese Household Income Project. The ordinary least squares estimation results show that a one-standard-deviation increase of prenatal exposure to total suspended particulates (TSPs) lowers math scores by 0.27 standard deviations and lowers language scores by 0.22 standard deviations for children aged between 6 and 19. The two-stage least squares estimation results show that a one-standard-deviation increase in TSP in utero lowers math scores by 0.31 standard deviations and lowers language scores by 0.53 standard deviations. The detrimental impact of prenatal exposure to air pollution becomes more apparent as the child ages. Air pollution exposure in utero has a more significant adverse effect than does exposure to air pollution in later childhood. The findings in this study provide additional evidence supporting the "fetal origins" hypothesis, which predicts early shocks in utero affect outcomes later in life.

Keywords: air pollution; cognitive skills; human capital; China; fetal origin

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1 Introduction

Air pollution is commonly associated with adverse health conditions. Epidemiological studies suggest that children are particularly vulnerable to ambient pollutants. High air pollution leads to more physical and mental problems for children (Evans, 2003; James Gauderman et al., 2000; Romieu et al., 1996). However, few studies have measured the detrimental impact of air pollution on the cognitive ability and academic performance of youth. Since Chinese air quality is notoriously poor, a natural question is "what is the impact of air pollution on cognitive development of Chinese youth?". While air pollution is a consequence of the economic development of China, pollution could also hinder future growth if it lowers the cognitive potential of the next generation. The purpose of this paper is to explore the long-term effect of prenatal exposure to air pollution and the cognitive development of youth in China.

Early life shocks can have both immediate and persistent adverse impacts on life outcomes. Barker and Osmond (1986) were the first to argue that adverse conditions as early as conception might lead to future diseases, and Barker (1990) firstly proposed the "fetal origins" theory. Since then, many epidemiology studies have found that adverse shocks in utero hurt neonatal health [1] . In the study of economics, Currie and Hyson (1999) evaluated the effect of low birth weight on economic success in adulthood. Since then, air pollution in utero has been associated with various health consequences for children, including asthma (McConnell et al., 2002), infant mortality (Chay and Greenstone, 2003,?; Currie and Neidell, 2005; Tanaka, 2015) and low birth weight (Currie and Hyson, 1999; Currie and Walker, 2011; Currie and Schmieder, 2009; Bharadwaj et al., 2014). Almond and Currie (2011) summarized the development of the economic study of 'fetal origins' theory.

Health early in life has been associated with cognitive development and human capital outcomes (Case and Paxson, 2008, 2009; Currie et al., 2010; Figlio et al., 2014;

[1] See Barker (1995); Gluckman and Hanson (2009); Eriksson et al. (2001); Hanson et al. (2014).

Persico et al., 2019). Miguel and Kremer (2004) found that early treatment for intestinal worms improved children's health and reduced absenteeism in schools. Baird et al. (2016) showed that adults who had received deworming treatments early in life worked more hours and earned 20% higher wages. Reyes (2011) evaluated the impact of early exposure to lead on cognitive development. She found that elevated levels of blood lead in early childhood are shown to adversely impact standardized test performance in Massachusetts. Maluccio et al. (2009) found that early childhood nutritional intervention improved reading and nonverbal cognitive ability and raised adult earnings for both women and men. Early exposure to high temperatures had a long-term impact on human capital accumulation and productivity later in life (Fishman et al., 2019).

Prenatal exposure to air pollution could also affect cognitive ability and impede human capital formation, especially academic performance. Sanders (2012) was the first to study the impact of prenatal exposure to air pollution on the cognitive development of youth. He found a significant detrimental effect of prenatal exposure to air pollution on the academic performance of youth in Texas during the 1980s. Bharadwaj et al. (2017) evaluated the impact of prenatal exposure to air pollution on cognitive ability using survey data of siblings. By exploiting the variation in prenatal exposure to air pollution between siblings, they found that prenatal exposure adversely affected academic performance in later childhood. Nevertheless, only a few studies have examined the long-term impact of air pollution on human capital formation, especially for developing countries that have huge populations and severe air pollution.

This study uses data on Chinese regional air pollution during 1981-2004, compiled by the World Bank, and information from a survey conducted in 2008 to show how total suspended particulates (TSPs) in utero affect later academic performance and cognitive skills for the children aged between 6 and 19. The Chinese Household Income Project (CHIP) 2008 contains the information of individual students from thirteen cities in nine provinces in China. It includes academic performance in mathematics and literature for individual students. The air pollution is matched with the sample of CHIP

2008 based on the city codes. The analysis controls other possible confounding factors, including household characteristics, school features, economic demographics and weather conditions. Ordinary least squares (OLS) estimation and two-stage least squares (2SLS) estimation are used to test three hypotheses derived from a theoretical model built on Currie et al. (2010). This study finds that early exposure to air pollution in utero has a significant detrimental impact on youth cognitive skill development. The effect of prenatal health shock on human capital becomes more apparent as the child ages. Early health shocks also have a more significant impact than late shocks on human capital outcomes since early shocks accumulate over time. The OLS estimation results show that a one-standard-deviation increase of prenatal exposure to total suspended particulates lowers math scores by 0.27 standard deviations and lowers language scores by 0.22 standard deviations. The 2SLS estimation results show that a one-standard-deviation increase in prenatal exposure to TSPs reduces math scores by 0.31 standard deviations and lowers language scores by 0.53 standard deviations.

This research contributes to the literature in three ways. First, it adds to the current literature about the long-term adverse impact of air pollution on academic performance (Sanders, 2012; Bharadwaj et al., 2017). By using detailed survey data, this paper provides the micro-foundations supporting the "fetal origins" hypothesis, controlling for heterogeneity at the individual student level. This study finds that prenatal exposure to TSPs has a significantly negative effect on the cognitive development.

Second, this is among the first studies examining the impact of air pollution on cognitive development in China. The only similar work is Zhang et al. (2018) [2], which measures the transitory and accumulative impact of air pollution on cognitive development . This study, however, examines the effect of prenatal exposure to air pollution. If damage to cognitive potential persists and accumulates over a person's lifetime, these

[2] Zhang et al. (2018) conducted a panel study by linking the CFPS 2010 and CFPS 2014 with the air pollution indexes (APIs) provided by the Chinese Environment Department. Their research focuses on the impact of air pollution on the cognitive skill development across ages. They found a one-standard-deviation increase in the API within a week lowers test scores by 1.6%, and it lowers math scores by 0.6%.

external costs will lower potential individual welfare and future economic growth due to human capital loss.

Third, this study is the first to test the cognitive impact of early exposure in utero and after-birth exposure to air pollution simultaneously. By doing so, it compares the relative importance of the two. This study finds that prenatal exposure to air pollution dominates after-birth exposure.

This paper is organized as follows. Section 2 provides a background on Chinese air pollution and reviews previous studies on the detrimental impact of air pollution on brain functioning and cognitive skill development. Section 3 describes the data used in this study. Section 4 introduces the theoretical model and empirical specifications. Section 5 presents the empirical results. The discussion and concluding remarks are given in section 6.

2 Background

2.1 Chinese air pollution

China has severe air pollution problem. The ambient concentration of total suspended particulates (TSPs) between 1981 and 2001 was five times the level in the United States before the passage of the Clean Air Act in 1970. Hazardous pollutants have caused both economic and noneconomic damage. Zhang et al. (2008) estimated that the total economic cost in China caused by PM10 [3] was approximately $30 billion in 2004. He et al. (2019) found that air pollution significantly reduced worker's productivity in China. In addition, life expectancy has been shortened by three years due to air pollution in northern China (Chen et al., 2013). The air quality has improved since the 2008 Olympic Games, but air pollution levels are still high. The average concentration of PM 2.5 [4]

[3] Airborne particulate with a diameter smaller than 10 micrometers. One micrometer = 10-6 meter.
[4] Airborne particulate with a diameter smaller than 2.5 micrometers.

in Beijing was 155 $\mu g/m^3$ in the winter of 2016 [5], approximately 16 times the WHO standard.

2.2 Air pollution, brain functioning and cognitive ability development

Most research on the health consequences of air pollution came from epidemiology. Air pollution causes brain damage through the respiratory system, leading to more inflammation an(Calderón-Garcidueñas et al., 2002; Costa et al., 2014; Fonken et al., 2011). Air pollution also affects genetic expression, which controls brain function (Risom et al., 2005; Calderon-Garciduenas et al., 2003).

Most economic research focuses on the contemporaneous impact of air pollution on the cognitive ability and academic performance of youth. For example, Zweig et al. (2009) found a negative short-term cognitive impact of air pollution caused by fuel combustion in California. Lavy et al. (2014) observed a detrimental impact of air pollutants (PM2.5 and CO) on the academic performance of students in Israel. Recent research (Liu and Salvo, 2018; Chen et al., 2018) analyzed the increase in student absences in schools when air pollution is severe in China. Zhang et al. (2018) utilized a rich sample and studied the transitory and cumulative impact of air pollution on cognitive development in China. They found that cognitive skills are negatively correlated with the average air pollution level within three years.

Bharadwaj et al. (2017) found an adverse impact of exposure to air pollution in utero after controlling for the fixed effect among twins. Sanders (2012) (2012) studied the impact of prenatal exposure to TSPs on educational outcomes using county-level variations in air quality in Texas. From his cross-sectional analysis, he found that a standard deviation decrease in TSPs in utero is associated with a two percent increase in school test scores for OLS estimation and 6% for his 2SLS estimation.

[5] Data Source: Air quality data of U.S. embassy in Beijing, China. This data is available since 2008.

3 Data

This study combines several data sources to evaluate the adverse cognitive impact of prenatal exposure to air pollution. This study evaluates the impact of prenatal exposure to TSPs for kids aged between 6 and 19 in 2008, and that is the typical age range for Chinese kids attending primary and secondary schools. In other word, the sample contains the students who were born between 1989 and 2002, and they were attending primary or secondary schools in 2008.

3.1 Air pollution data

The World Bank's Development Economics Research Group (DECRG) collaborated with China National Environmental Monitoring Stations to provide Chinese air pollution data from 1981 to 1995. The China Environmental Yearbooks provide the same data from 1990 to 2004. I combine these two series for three measures of air pollution: total suspended particulates, sulfur dioxide, and nitrogen oxide. The air pollution data report these three air pollutants for the period 1981-2004. The suspended particulates are atmospheric particulate matter (PM) with a diameter of smaller than 100 micrometers and containing large particles such as pollen and finer matter produced by industry and fuel combustion. It is also called PM100 in the way that PM 10 and PM 2.5 are defined. Figure 1 illustrates the data availability of air pollution in China. Before 2004, TSPs, sulfur dioxide and nitrogen oxide were the only available measures of air pollution in China. The government has reported the air pollution index (API), which lists the amounts of various pollutants, including TSPs, sulfur dioxide and nitrogen oxide, since 2005. The U.S. embassies have reported the PM 2.5 levels of multiple cities since 2008. The currently used air quality index (AQI) was introduced in 2013, and PM 2.5 have also been available since then.

Figure 2 shows the geographic locations of all thirteen cities studied in this paper. Most cities are in southern China, away from Beijing. Figure 3 shows the time series data on total suspended particulates for multiple cities in the sample. TSPs level was particularly severe at the beginning of the 1980s. Air quality improved during the 1990s and has remained relatively constant at 100-250 $\mu g/m^3$ since 2000. As the statistical summary lists in Table 1, the average total suspended particulates at birth is approximately 256 $\mu g/m^3$, which is very high compared with the U.S. Environmental Protection Agency standard (45 $\mu g/m^3$ in 1971). Figure 4 illustrates the distribution of three different air pollutants in the sample. The prenatal exposure to TSPs ranged between 0.087 mg/m^3 (or 87 $\mu g/m^3$) and 0.815 mg/m^3 (or 815 $\mu g/m^3$).

Figure 5 illustrates the distributional pattern in the concentration of TSPs, sulfide dioxide, and nitrogen monoxide by different years in the period 1989-2002. The level of TSPs concentration has a decreasing trend and the variations between years and cities are sizeable. Figure 6 shows the correlation between every two types of air pollutants among TSPs, sulfide dioxide, and nitrogen monoxide. It shows that TSPs and SO2 are correlated, and TSPs and NOx are also correlated with each other while not as close as TSPs and SO2.

Although Chinese government data on air pollution may be suspect, Chen et al. (2013), who used similar data with this study, reported that the data quality is not a critical issue. For the period of their study, government officials' evaluations were primarily based on economic growth rather than environmental indices. Moreover, the statistics were not widely available at that time, which reduced the incentive to publish inaccurate information. This study corrects for the potential bias from mismeasured pollution using an instrumental variable estimation and compares the empirical results to the ordinary least-squares estimate.

3.2 Test scores and household demographics

Individual test scores were obtained from the 2008 Chinese Household Income Project (CHIP). The dataset provides detailed household demographics, including parents' information (e.g., income and education), children's characteristics (e.g., age, gender, birth order, and educational expenditure), and schools' features (e.g., school quality and type). The CHIP data contains the language and mathematics exam scores of students from thirteen cities in nine provinces. The study focuses on children aged 6 to 19 who are in primary and secondary schools. CHIP 2008 separates all observations into three subsamples: urban nonmovers, migrants, and rural nonmovers. Since almost all air pollution monitors are located in urban areas and to avoid misusing pollution exposure due to migration (Banzhaf and Walsh, 2008), this study first focuses on urban nonmovers and then tests a supplemental subsample of migrants in the same cities. The language and math test scores are converted into standard scores (i.e., z-value) based on school grades to make the scores comparable among students from different school grades. That is, $Z_{ij} = \frac{s_{ij} - \bar{s_j}}{\sigma(s_j)}$.

The test score of individual student i who is at school grade j (e.g., the 1st year of elementary school or the 2nd year of high school) has an exam score s_{ij} (a percentage value). $\overline{S_j}$ is the average test score for the students at school grade j, and $\sigma(S_j)$ is the standard deviation of the test scores of students at school grade j. Figure 7 shows the distribution of standardized math and language scores. The range of math test scores is (-7.744, 1.909), and the range of language test scores is (-5.626, 2.276). Figure 8 shows the distribution of math test scores and language test scores by birth years, and it also illustrates the correlation between prenatal exposure to TSPs and test scores. The top panel of Figure 8 shows a substantial variation in test scores of math and language. The bottom panel of Figure 8 implies an inverse correlation between prenatal exposure to TSPs and test scores.

Table 1 describes the data in this study. The information on the children includes their age, their gender, and their birth order. The education-related factors are school type, school quality, and educational expenditure. Other household characteristics include parents' education, annual income, and the number of children. CHIP also reports children's current height, weight, and health status, which measures children's health and physical maturity.

3.3 Weather factors, demographic data, health measures

Weather can be a confounding factor because of the correlation between air pollution and atmospheric characteristics. To isolate the impact of air pollution, several weather indicators are included in the analysis. The climatic data come from the China Meteorological Data Service Center (CMDC). They provide annual information about mean temperature, the number of days with precipitation, sunshine hours, humidity, wind speed, and ground atmospheric pressure of different cities. I include the mean temperature, sunshine hours, number of days with precipitation more than one centimeter, and humidity as covariates in the estimation. Table 1 reports the atmospheric features of the cities in this study. This study also includes economic demographics such as GDP per capita at birth and the time when exams were taken to control for potential confounding factors that would bias the measured relationship between pollution and test performance. The data are from the yearbooks of each city between 1989 and 2008. Table 1 contains a description of these factors. The GDP per capita at birth is 11636 CNY and 56520 CNY at test date after adjusting for inflation.

The other two atmospheric factors, wind speed, and ground atmospheric pressure serve as instrumental variables (IV) for air pollution. The current meteorology literature provides a correlation between air pollutants and weather conditions. Air pollutants tend to concentrate on a stable environment (Davis and Kalkstein, 1990). High air pollution concentrations are correlated with light wind speed (Niemeyer, 1960) and high air pressure (Chen et al., 2008; Cheng et al., 2007). High air pollutant concentrations usually occur in less windy and high ground pressure environments (Grundström et al., 2015). The underlying reason is that high ground pressure limits the dispersion of air pollutants and keeps air pollutants close to the ground. Environmental economic studies also use meteorological measurements as instrumental variables for air pollution. He et al. (2019) use weather measures including wind speed and ground temperature, as instruments for air pollutants and study the impact of air pollution on worker productivity.

This study also estimates the impacts of prenatal exposure to air pollution on the youth's current height, weight, and health status to examine whether air pollution also affects youth physical health. The current height and weight are normed with the national average of youths by different ages and genders. The national average height and weight are from the Yearbook of Health in China 2016, published by the National Health Commission of China.

After matching air pollution data with the household data, I have information about the children, their parents' and households' characteristics, the exposure to air pollution in utero and afterward, the school's features, and other weather conditions.

4 Conceptual Framework

Early shocks to fetal health have a potential impact on children's cognitive development trajectory (Cunha and Heckman, 2008; Conti et al., 2010; Currie et al., 2010). The initial human capital loss is compounded by the fact that current human capital is an input into subsequent human capital production. The model is built on Currie et al. (2010) to develop three hypotheses that can explain why initial shocks can have a larger impact later in life.

Suppose that the outcome function is:

$$S_t = aH_t^{\alpha}C_t^{\beta}$$

where S_t represents the test scores at time t, H_t is the health condition at time t, and C_t is the student's cognitive skills at time t. For simplicity, the model assumes the cognitive skill at time t is jointly determined by cognitive skills and health condition of period t-1, and it has a Cobb-Douglas function form. In addition, the health condition at time t is a power function of the health condition in period t-1 with a disturbing shock on health.

Using lower-case variables to designate logs, cognitive skill development follows:

$$c_t = b_0 + b_1 c_{t-1} + b_2 h_{t-1}$$

The contemporaneous health condition follows:

$$h_t = \gamma h_{t-1} + u_t$$

where $c_t = ln\left(C_t\right)$, $h_t = ln\left(H_t\right)$, and u_t is the disturbing shock to health at time t, such as air pollution. Without loss of generality, I suppose an individual has lived three periods.

Solving the model recursively to obtain (1):

$$ln\left(S_t\right) = \delta + \delta_1 c_{t-3} + \delta_2 h_{t-3} + \delta_3 u_t + \delta_4 u_{t-1} + \delta_5 u_{t-2} \tag{1}$$

The parameters on the right side can be expressed as (2):

$$\begin{cases} \delta_1 = \beta b_1^3 \\ \delta_2 = \left(\beta b_1^2 b_2 + \left[\left(\alpha\gamma + \beta b_2\right)\gamma + \beta b_1 b_2\right]\gamma\right) \\ \delta_3 = \alpha \\ \delta_4 = \alpha\gamma + \beta b_2 \\ \delta_5 = \gamma\delta_4 + \beta b_2 b_1 \end{cases} \tag{2}$$

From this model, the first-period shock may persist to later outcomes under some conditions, for example, $b_2 > 0$ and $\gamma = 1$. In this model, the early shock accumulates over time ($|\delta_5| > |\delta_4| > |\delta_3|$). In particular, u_1 represents the exposure to air pollution in utero. u_2 and u_1 are the exposures to air pollution after birth (i.e., in the period 2 and 3, respectively). c_0 and h_0 represent the cognitive ability and health condition at the beginning of conception. They are correlated with their parents' cognitive skills and health conditions. Here are the three hypotheses related to this model:

Hypothesis I: Early health shocks, e.g., air pollution, have an impact on later human capital formation, including cognitive skill and academic performance. This implies that $\delta_5 > 0$.

Hypothesis II: The impact of early health shocks on human capital becomes more apparent as the child ages. This implies $|\delta_5| > |\delta_4|$.

Hypothesis III: Early health shocks have a greater impact than late shocks on human capital outcomes since early shocks accumulate over time. This implies that $|\delta_5| > |\delta_3|$.

To test these three hypotheses embedded in (1), I control the exposure to air pollution in utero and afterward, c_0 and h_0. Because c_0 and h_0 are not directly observable, I use parents' education and income to control them. Therefore, the econometric specification is as follows:

$$S_{ibcl} = \delta_p P_{ib} + \beta X_i + \theta Z_{is} + \gamma Y_{ic} + \lambda_c + \pi_b + \varepsilon_{ibcl} \tag{3}$$

where S_{ibcl} represents S in the theoretical model, and it is the score of subject l for individual i who were born in year b in city c. The exposure to air pollution in utero, which represents the early health shocks as u_1 in the model, is denoted by P_{ib}. X_i are the characteristics of the student and his/her household, including the student's age, gender, age entering primary school, number of siblings, and parents' education and income. Z_{is} is the characteristics of the kid's school, including school quality and school type (e.g., public schools, private schools, and boarding schools.) Y_{ic} is the city characteristics including GDP per capita and weather factors. λ_c is the fixed effect of the birth city and π_b represent the fixed effect of his/her birth year. To allow heterogeneous correlation, the standard errors are double clustered by birth cities and birth years. δ_p represents the cognitive impact of prenatal exposure to TSPs.

The after-birth exposure to air pollution could mask the impact of prenatal exposure to air pollution, therefore I add a computed after-birth exposure to air pollution in (3). Suppose P_{iy} is the air pollution in age y after birth, $\sum_{y=1}^{a_i} P_{iy}$ represents the total cumulative exposure to air pollution after birth (a is the child's age). Because air pollution data of TSP are not available after 2004[6], the cumulative exposure can be computed as follows:

$$\sum_{y=1}^{a_i} P_{iy} = a_i \times \frac{1}{2004 - t_i^0} \sum_{t=t_i^0+1}^{2004} P_{it} \tag{4}$$

For student i who was born in the year t_i^0 , his/her accumulative exposure to this pollutant is equal to the product of age and average exposure after birth. a_i is the child's age. Since the test scores reported in CHIP were taken in 2008, it is obvious that $a_i = 2008 - t_i^0$. Figure 3 shows that air pollution is more severe in the early years, which implies a potential positive measurement error in the computed accumulative exposure. However, this potential bias would not change the conclusion about the adverse impact of prenatal air pollution exposure. If the accumulative exposure to air pollution is positively correlated with prenatal exposure and accumulative exposure also depresses cognitive development, an overestimated accumulative exposure will absorb the impact of prenatal exposure. The magnitude and significance of prenatal exposure then decrease. The results of this study provide a lower bound of the adverse impact of prenatal exposure.

Hypothesis I can be directly tested from the estimation of (3), and the sign of the coefficient of P_{ib} represents the impact of prenatal exposure to TSPs on test scores.

Hypothesis II indicates that the adverse impact of prenatal exposure becomes more prominent because the early shock accumulates over time. The best strategy of verifying hypothesis II is estimating the effect of prenatal exposure at different ages and checking the magnitude of the impact over time. But the test scores are only available from one cross-sectional survey (i.e., CHIP 2008). However, if the parameters in (2) are

[6]For the availability of air pollution data, please see Figure 1.

not fundamentally different among different cohorts[7], *Hypothesis II* can be tested in an alternative way. Under this assumption, an interaction term between prenatal exposure to TSPs and the birth year dummy variable is added in (3). From *Hypothesis II*, the magnitude of coefficient δ is expected to be greater among the older cohort.

Hypothesis III can be indirectly tested by comparing the magnitudes of the estimated coefficients of $\sum_{y=1}^{a_i} P_{iy}$ and P_{ib} , evaluated at the mean value. In addition, I add the exposures to TSPs after birth in estimation (5) to verify *Hypothesis III* directly:

$$S_{ibcl} = \delta P_{ib} + \sum_{y=1}^{4} \delta_y P_{iy} + \beta X_i + \theta Z_{is} + \gamma Y_{ic} + \lambda_c + \pi_b + \varepsilon_{ibcl} \tag{5}$$

The exposures to TSP between ages 1 and 4 are added in the estimation of (4), and *Hypothesis III* holds if the magnitude of δ_p is greater than δ_y, $\forall y \in (1, 4)$.

5 Empirical results

5.1 OLS and 2SLS estimation results

The following regressions control school quality, school type, parents' education and income, city economic demographics, and children's characteristics in all regressions. In all regressions, the error terms are double clustered by cities and birth years. When accumulative exposure to TSP is added, birth year fixed effects are not controlled to avoid the multicollinearity problem.

This study first tests *Hypothesis I*, which states that early exposure to air pollution in utero has an adverse impact on the academic performance of students. Table 2 lists the empirical results of (3) using mathematics and language test scores as the dependent variables. I use prenatal exposure to TSPs as the measure of prenatal air pollution expo-

[7]It means δ_p in year t for cohort a is equal to δ_p in year t+j for cohort b, and the cohort a is j years older than cohort b.

sure, and the other two types of air pollutants, sulfur dioxide, and nitrogen oxide will be added into the estimation in the section of heterogenous tests. The first four columns of Table 2 do not include accumulative exposure to TSP, and it is added in Columns 5 and 6. As Columns 1 and 2 of Table 2 show, a one-standard-deviation (119 $\mu g/m^3$) increase in the exposure to total suspended particulates in utero will lower math scores by 0.21 standard deviations (i.e., $119/1000 \times 1.756 = 0.21$) and lower language scores by 0.20 standard deviations. Then, weather factors are added into the regressions in Column 3 and 4 of Table 2. From the estimation results in Column 3 and 4, a one-standard-deviation increase in prenatal exposure to TSP lowers math scores by 0.27 standard deviations and lowers literature scores by 0.22 standard deviations after adding the weather factors. The increasing magnitudes of the coefficient indicate that the weather variables are correlated with pollution indicators such that excluding the confounding effects of weather understates the estimated pollution effects. In Columns 5 and 6 of Table 2, both prenatal exposure to TSP and accumulative exposure after birth are added into the estimation of (3). A one-standard-deviation increase in prenatal exposure to TSP lowers math scores by 0.23 standard deviations and lowers language scores by 0.20 standard deviations. These results support *Hypothesis I* that early exposure to air pollution in utero has an adverse impact on academic performance and cognitive development in later life. At the same time, the results in Columns 5 and 6 provide indirect evidence supporting *Hypothesis III* that exposure to air pollution in utero has a more significant impact than later exposures after birth. The coefficient of accumulative exposure to TSP is not substantial, while its sign is negative. With a one-standard-deviation increase in accumulative exposure to TSP, math scores will be lowered by 0.23 standard deviations (i.e., $1.471 \times 0.156 = 0.229$), and language scores will drop by 0.14 standard deviations, which is smaller than the impact of prenatal exposure to TSP. The other two types of air pollutants, sulfur dioxide, and nitrogen oxide, will be added into the estimation in the section of heterogeneous tests.

To verify the causality between prenatal exposure to air pollution and test scores and address the concern about measurement error in prenatal exposure to air pollution, the two-stage least square approach is adopted in this study. Previous environmental economic studies use atmospheric measures as instrumental variables for air pollution (Arceo et al., 2016; He et al., 2019). The current meteorology literature provides a correlation between air pollutants and weather conditions. Air pollutants tend to concentrate on a stable environment where wind speed is low and air pressure is high. As such, two weather factors are used as instrumental variables for air pollution: the average wind speed and the ground atmospheric pressure of the birth year. Column 7 and 8 of Table 2 report the two-stage least squares estimation results. Math test scores and language test scores were adversely affected by prenatal exposure to TSPs, while the effect on math test scores is not statistically significant. A one-standard-deviation increase in prenatal exposure to TSPs reduces math test scores by 0.31 standard deviations, and it reduces language test scores by 0.53 standard deviations. The first stage results are reported in Table A1 in the appendix. The accumulative exposure to TSPs is added in the two-stage least squares estimation, and the results are put in Table A2 in the appendix.

As mentioned in the previous section, an interaction between prenatal exposure to TSPs and birth year dummy variables are added into the estimation of (3) to test *Hypothesis II*. If the second hypothesis holds, the adverse impact of early exposure to air pollution will be more prominent for the older cohort. Table 3 reports the empirical results for verifying *Hypothesis II*. Column 1 and 2 of Table 3 report the OLS estimation results. The adverse effect of prenatal exposure to TSPs on test scores is more obvious for older cohorts. Cohorts born between 1989 and 1996 (i.e., aged between 12 and 19) were significantly affected by prenatal exposure to TSPs for both math test scores and language test scores. The two-stage least squares estimation is also used, and column 3 and 4 in Table 3 illustrate the results. Empirically, following Aghion et al. (2005), interactions of instrumental variables and birth year dummies are added into the 2SLS estimation. The empirical results of the 2SLS estimation show that adverse cognitive impacts caused by prenatal exposure to TSPs are more pronounced among older cohorts. Figure 9 illustrates the 95% confidence interval of the estimated effects of prenatal exposure to TSPs. The upper panel shows estimated heterogeneous impacts from OLS estimation, and the bottom panel depicts the estimated effects of 2SLS estimation. For math test scores, the OLS estimation results shows that adverse cognitive impact is more obvious among older cohorts who were born between 1989 and 1996. The two-stage least squares estimation shows that the kids aged at 18 and 19 were significantly affected by prenatal exposure to TSPs, while younger kids were not significantly affected. For language test scores, the adverse impact brought by prenatal exposure to TSPs is always more pronounced for older cohorts (especially for the kids born between 1989 and 1996), from the results of both OLS estimation and 2SLS estimation. These results support our *Hypothesis II* that the impact of early health shocks on human capital becomes more apparent as the child ages.

To test *Hypothesis III*, children's exposures to air pollution after birth are added to the analysis using (5). The detrimental impact of prenatal exposure to air pollution is expected to be stronger than exposure to air pollution later in life, i.e., $|\delta_p| > |\delta_y|, \forall y \in (1, 4)$.

Table 4 shows how exposure to air pollution at different stages in life affects the students' test scores. The empirical results show that exposure to air pollution in utero has a larger and more significant impact on test scores than exposure later in life. A one-standard-deviation increase in prenatal exposure to air pollution leads to a 0.52-0.64 standard deviation decrease in math scores and a 0.29-0.35 standard deviation decrease in language scores. The exposures after birth, meanwhile, have a smaller detrimental impact on cognitive development. These results support *Hypothesis III* that the effects of exposure to air pollution after birth are smaller than the effect of exposure to air pollution in utero, although most effects of pollution on academic performance later in life are also negative. Therefore, prenatal exposure to air pollution has a greater detrimental impact on the cognitive development of youth than later exposures in life.

5.2 Heterogeneous tests

Current research has found that air pollution has differential impacts in utero depending on fetal maturity (Currie and Schwandt, 2016). The effect is most significant for the first trimester of gestation. Since CHIP 2008 does not collect the length of the gestation period, the first trimester may occur in the year before the actual birth year. I add the TSPs of the year before birth into the regression and test the joint impact of early exposures to TSPs. Table 5 illustrates how exposure to TSPs around birth affects children's cognitive ability later in life. With a milligram (i.e., 1 mg, or 1000 μg) increase in TSPs of both exposures to TSPs, math scores experience a significant drop by 2.01-2.29 standard deviations, while language scores drop by 1.63-1.89 standard deviations. Note that prenatal exposure to air pollution in the birth year still has a significant detrimental impact on test scores.

In the theoretical model, early exposure to air pollution affects cognitive development because it adversely affects youth health. Case and Paxson (2008) regarded height as a measure of health and found that it correlated with future earnings and cognitive skills. In this sense, exposure to air pollution early in life may have an adverse effect on youth development other than the test scores in schools. Three measures of current health are used in the following estimation: current height, weight, and self-reported health status compared with peers at the same age. Current weight and height are weighted by national average values by ages and genders. In the survey of CHIP 2008, respondents were asked to answer the question "how do you evaluate your current health compared with your peers at the same age". Answers to this question are such as "Excellent", "Good", "Average", "Poor", and "Very Poor". Since the answers of "Poor" and "Very Poor" are very few, I group the last three categories into one representing "poor health". In general, the higher value of this variable indicates a worse health status. The OLS estimation is used for evaluating the impact on weight and height, and an ordered Probit model is used for evaluating health status. Table 6 shows that prenatal exposure to TSPs negatively affects the child's current height, while the impact is not significant. Meanwhile, the accumulative exposure to TSPs adversely affects youth weight and height. Prenatal exposure to TSPs also negatively affect current health status, while the impact of accumulative exposure to TSPs is opposite and not significant. These results indicate that early air pollution exposure hurts youth maturity and health, which further affects the cognitive development of youth.

Table 7 includes two additional measures of air pollution. The air pollution dataset provides two other types of air pollutants, SO2 and NOx. These two measures have more missing values than do TSPs. In this step, these two types of air pollutants are added into the analysis, and Table 7 reports the estimation results using (3). The first four columns report the impact of each air pollutant on math and language test scores. There is no significant impact of prenatal exposure to SO2 or NOx on test scores. Columns 5 and 6 list the estimation results with all three measures of prenatal exposure to air pollution, and only the exposure to TSPs significantly adversely affects math and language scores. In the last two columns of Table 7, the cumulative exposure of three pollutants is added. Still, only prenatal exposure to TSPs will significantly affect the cognitive ability of youth later in life. These results indicate that the negative cognitive impact of prenatal exposure to air pollution is mostly from TSPs rather than SO2 and NOx. The estimations in previous section, which focus only on TSPs, are not biased by excluding SO2 and NOx.

Migration is another concern of this study because households may make their choices by feet when there is severe air pollution. First, if those who migrate because of air pollution are more sensitive to air pollution, then the analysis focusing on urban nonmovers gives a lower bound of the adverse impact of air pollution exposure. Second, if those who migrate because of severe air pollution are less sensitive to air pollution, then the remaining individuals are more susceptible to air pollution. Thus, focusing on urban nonmovers may exaggerate the impact of air pollution. The second scenario mostly occurs when those migrants come from wealthier households who took more avoidance behavior and therefore were less exposed to air pollution by any means. To address the migration issue, the migrant's subsample of CHIP 2008 is included[8]. Table 8 lists the empirical results with the migrants in the cities. The migrant's sample of CHIP 2008 does not report the original place where these migrants come from. I assume the children who spend all year with their parents and study in the same city were born in the destination city. It is a strong but reasonable assumption. First, people are less likely to migrate when they have offspring. Moreover, it is very difficult and expensive for a Chinese child to attend a local school if he/she was not born in the same city. Table 8 reports the estimation results with migrant children. Column 1 and 2 in Table 8 show that prenatal exposure to TSPs also adversely affects test scores of migrant children with OLS estimation or 2SLS estimation. From OLS estimation results in the upper panel of Table 8, an one-milligram increase in prenatal exposure to TSPs will lower math scores by 3.84 standard deviations and lower language scores by 3.64 standard deviations, which is larger in magnitude compared with the impact on urban nonmovers. Columns 3 and 4 of Table 8 report the estimation with all children. The results indicate a significant negative impact of prenatal exposure to TSP on the test scores. These results suggest that the findings in the previous section are not fundamentally changed by self-selected migration. A hackman selection procedure is added in the last two columns of Table 8, in which an inverse mills ratio calculated from a migration equation is added in the second stage. The migration equation result is reported in Table A3 in the appendix. The migration decision is presumed to be determined by how many siblings that parents have, the birth ranks of parents, history of marriage and fertility, and ethnicity.

Table 9 further provides the estimation among different households differentiated by household wealth to address the concern of avoidance behavior. The households of each city are separated into three groups: wealthy households who are in the upper one-third, poor households who are in the bottom one-third, and middle-class households whose income is between the wealthy and the poor. Table 9 reports the heterogeneous impact of prenatal exposure to air pollution on cognitive ability. There is no significant difference in the impacts of prenatal exposure to air pollution among children from

[8]The data summary of migrant sample is included in Table A6 in the appendix.

different households.

In Table 10, seasonal factor variables are added to the estimation. Since air quality is usually worse in winter than average time, the kids whose mothers are pregnant in the winter are more affected and the adverse impact of prenatal exposure to TSPs should be more obvious. The whole year is separated into four seasons: season 1 (January-March), season 2 (April-June), season 3 (July-September), and season 4 (October-December). For the kids who were born in the fourth season, their mothers were pregnant in the previous winter (i.e., December-February)[9], and they are more sensitive to prenatal exposure to TSPs. Table 10 reports the estimation results, which show that the adverse impact of prenatal exposure to TSPs is more pronounced among the kids whose mother was pregnant between December and February.

I also test the gender differences of the cognitive impact of prenatal exposure to TSPs in Table A4 in the appendix. Table A5 in the appendix reports the effects of TSPs exposures around the birth year. The findings concluded above, that there exists an adverse cognitive impact of prenatal exposure to TSPs, do not fundamentally change in these heterogenous tests.

6 Conclusion

This study finds a significant adverse impact of prenatal exposure to total suspended particulates on the cognitive development of youth in China. The OLS estimation results show that a one-standard-deviation increase of prenatal exposure to total suspended particulates lowers math scores by 0.27 standard deviations and lowers language scores by 0.22 standard deviations. The 2SLS estimation result shows that a one-standard-deviation increase in TSP in utero reduces math scores by 0.31 standard deviations and lowers language scores by 0.53 standard deviations, while the impact on math test scores is not significant. The adverse impact of prenatal exposure to air pol-

[9]The gestation period is assumed to be 40 weeks, that is about 10 months.

lution is more substantial in magnitude and more significant than exposures later in life. The negative effect of prenatal exposure becomes more prominent as the child ages. Moreover, air pollution has a profound impact on youth health and maturity. Youth health and maturity are negatively affected by prenatal exposure to air pollution. These results support the "fetal origins" theory that early shocks in utero have a great impact on outcomes in later life.

Although this study has explained some mechanisms by which early air pollution exposure may affect the later human capital outcome, the picture is not clear enough. Future work needs to include more information about children's health conditions throughout their childhood. For example, Currie et al. (2010) test how the health conditions in different ages of the same child affect young adult outcomes. In addition, it is interesting to test how severe air pollution will affect the behavior and noncognitive skill development of youth.

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Table 1: Data summary

	Observation	Mean	S.D.	Min	Max
z-score math	1003	0.031	0.948	-7.744	1.909
z-score language	1003	0.027	0.928	-5.626	2.276
Prenatal exposure to TSPs (mg=1000μg)	1003	0.256	0.119	0.087	0.815
TSPs exposure in the year before birth year	997	0.271	0.132	0.09	0.96
SO2 exposure in birth year	983	0.058	0.03	0.007	0.183
NOx exposure in birth year	939	0.069	0.03	0.007	0.152
Accumulative exposure of TSPs after birth	965	2.797	1.471	0.696	9.163
Accumulative exposure of SO2after birth	1003	0.627	0.329	0.086	1.869
Accumulative exposure of NOx after birth	1003	0.763	0.358	0.165	2.094
TSPst+1 (TSPs of the year after birth year)	960	0.248	0.112	0.087	0.72
TSPs t+2	890	0.243	0.106	0.087	0.633
TSPs t+3	824	0.237	0.105	0.087	0.633
TSPs t+4	744	0.233	0.101	0.087	0.571
GDP per capita birth year (in 2008 Yuan)	1003	11891.57	8547.655	1111	34822
GDP per capita in 2008	1003	57168.07	18808.12	19924	83431
Mean temperature in 2008	1003	17.765	2.622	14.4	22.8
Ln (Father's annual income)	1003	5.941	3.479	0	10.309
Ln (Mother's annual income)	1003	4.895	3.599	0	9.798
Father's years of education	1003	11.935	3.432	0	31
Mother's years of education	1003	11.164	3.319	0	35
Gender (Girls=1)	1003	0.479	0.5	0	1
Number of siblings	1003	0.352	0.65	0	3
Birth order	1003	1.066	0.264	1	3
Attending average school	1003	0.345	0.476	0	1
Attending better than average school	1003	0.511	0.5	0	1
Attending worse than average school	1003	0.009	0.094	0	1
Attending best school	1003	0.135	0.341	0	1
Attending public School	1003	0.928	0.258	0	1
Attending private School	1003	0.068	0.252	0	1
Attending boarding school	1003	0.143	0.35	0	1
Expenditure on tutoring classes	1003	1220.212	2363.078	0	36100
Current Height (cm)	1176	156.803	16.016	92	198
Current Weight (kg)	1176	48.662	13.512	19	105
Current health, Excellent	1176	0.196	0.397	0	1
Current health, Good	1176	0.656	0.475	0	1
Current health, Poor	1176	0.148	0.355	0	1
Days with precipitation above 0.1cm	843	123.068	26.269	48	172
Average temperature (C^o)	872	17.605	2.816	13.9	23.8
Humidity (%)	843	75.243	4.422	61	86
Annual sunshine hours	843	1768.193	297.745	818.6	2372.2
Wind Speed (m/s)	843	2.237	0.682	1	3.4
Atmospheric pressure (hPa)	843	1030.453	16.383	972.6	1045.7
Birth year	1003	1995.388	3.573	1989	2002

Source: China Household Income Project 2008, World Bank's Development Economics Research Group (DECRG), China Environmental Yearbooks, China Meteorological Data Service Center (CMDC), Yearbook of Health in China 2012, and GDP data comes from the city's yearbooks.

Table 2: Prenatal exposure to TSPs and test scores

	(1) OLS Math	(2) OLS Language	(3) OLS Math	(4) OLS Language	(7) OLS Math	(8) OLS Language	(5) 2SLS Math	(6) 2SLS Language
Prenatal exposure to TSPs	-1.756***	-1.681***	-2.243***	-1.856***	-1.917**	-1.644**	-2.802	-4.380**
	(0.571)	(0.455)	(0.716)	(0.558)	(0.807)	(0.767)	(2.180)	(2.137)
Accumulative exposure to TSPs after birth					-0.156*	-0.099		
					(0.081)	(0.069)		
Gender(girl=1)	-0.040	0.138**	-0.046	0.155**	-0.067	0.156**	-0.040	0.173***
	(0.056)	(0.058)	(0.064)	(0.067)	(0.067)	(0.068)	(0.064)	(0.063)
Ln(father's income)	-0.012	-0.002	-0.005	0.002	-0.008	0.005	-0.010	-0.004
	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.010)
Ln(mother's income)	0.003	0.007	0.002	0.008	-0.003	0.001	-0.003	0.004
	(0.008)	(0.009)	(0.009)	(0.011)	(0.009)	(0.010)	(0.010)	(0.010)
father's years of education	0.023**	-0.005	0.019*	-0.007	0.019	-0.009	0.016	-0.007
	(0.010)	(0.012)	(0.011)	(0.013)	(0.012)	(0.014)	(0.013)	(0.013)
mother's years of education	0.011	0.022*	0.017	0.023	0.019	0.023	0.018	0.022*
	(0.013)	(0.013)	(0.014)	(0.014)	(0.015)	(0.015)	(0.014)	(0.013)
Attending better than average school	-0.246***	-0.205**	-0.213**	-0.166*	-0.231**	-0.184**	-0.212**	-0.174*
	(0.081)	(0.086)	(0.088)	(0.092)	(0.089)	(0.093)	(0.096)	(0.094)
Attending average school	-0.417***	-0.392***	-0.395***	-0.384***	-0.431***	-0.386***	-0.393***	-0.396***
	(0.096)	(0.094)	(0.100)	(0.103)	(0.102)	(0.099)	(0.105)	(0.103)
Attending worse than average school	-0.773	-1.384**	-0.745	-1.358**	-0.654	-1.507**	-0.762**	-1.368***
	(0.550)	(0.574)	(0.564)	(0.573)	(0.593)	(0.628)	(0.316)	(0.310)
Attending private School	-0.153	-0.102	-0.269	-0.068	-0.246	-0.030	-0.247*	-0.031
	(0.179)	(0.141)	(0.219)	(0.173)	(0.225)	(0.183)	(0.133)	(0.130)

Table 2 continued: Prenatal exposure to TSPs and test scores

	(1) OLS Math	(2) OLS Language	(3) OLS Math	(4) OLS Language	(7) OLS Math	(8) OLS Language	(5) 2SLS Math	(6) 2SLS Language
Attending non-boarding school	0.015	0.087	0.006	0.073	0.057	0.129	0.013	0.092
	(0.110)	(0.099)	(0.117)	(0.105)	(0.118)	(0.110)	(0.105)	(0.103)
Expenditure on tutoring classes	-0.000	0.000	-0.000	0.000	-0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Days with precipitation above 0.1cm			-0.000	-0.006	-0.000	-0.007	-0.003	-0.008
			(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Average temperature (Co)			0.043	-0.104	0.082	0.038	0.007	0.024
			(0.198)	(0.186)	(0.087)	(0.075)	(0.227)	(0.223)
Humidity (%)			0.024	0.017	0.020	0.031	0.012	0.048
			(0.042)	(0.036)	(0.029)	(0.030)	(0.050)	(0.049)
Annual sunshine hours			0.001*	0.000	0.000	0.000	0.001	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Birth Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Birth City FE	Y	Y	Y	Y	Y	Y	Y	Y
N	1003	1003	843	843	809	809	843	843
Adjusted-R2	0.099	0.109	0.111	0.112	0.084	0.096	0.105	0.092

Notes: All estimations above control school grade fixed effects, the number of siblings, birth orders, cities' GDP per capita in the birth year and test year (2008), and the average temperature in 2008. Error terms are double clustered by birth cities and birth years. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level. The first stage of 2SLS estimation is reported in the appendix.

Table 3: Prenatal exposure to TSPs and test scores by birth years

	(1) OLS Math	(2) OLS Math	(3) 2SLS Language	(4) 2SLS Language
Prenatal exposure to TSPs$\times I_{1989}$	-2.933***	-2.714*	-2.309***	-4.632***
	(0.794)	(1.469)	(0.772)	(1.433)
Prenatal exposure to TSPs$\times I_{1990}$	-3.005***	-3.268*	-2.409***	-5.402***
	(0.869)	(1.743)	(0.884)	(1.700)
Prenatal exposure to TSPs$\times I_{1991}$	-3.042***	-2.527	-2.761***	-5.507***
	(0.903)	(1.691)	(0.878)	(1.649)
Prenatal exposure to TSPs$\times I_{1992}$	-2.388***	-1.835	-1.753**	-3.840***
	(0.859)	(1.503)	(0.836)	(1.466)
Prenatal exposure to TSPs$\times I_{1993}$	-2.258**	-1.516	-2.053**	-4.012***
	(0.945)	(1.566)	(0.919)	(1.528)
Prenatal exposure to TSPs$\times I_{1994}$	-2.429**	-1.319	-2.486**	-4.134**
	(0.996)	(1.797)	(0.968)	(1.753)
Prenatal exposure to TSPs$\times I_{1995}$	-3.563***	-2.138	-3.177***	-4.366***
	(1.014)	(1.664)	(0.986)	(1.623)
Prenatal exposure to TSPs$\times I_{1996}$	-1.903**	-0.228	-1.868**	-2.429*
	(0.897)	(1.503)	(0.872)	(1.466)
Prenatal exposure to TSPs$\times I_{1997}$	-1.186	1.042	-1.325	-2.201
	(0.959)	(1.852)	(0.930)	(1.807)
Prenatal exposure to TSPs$\times I_{1998}$	-0.533	2.015	0.03	-0.783
	(1.088)	(2.183)	(0.671)	(2.129)
Prenatal exposure to TSPs$\times I_{1999}$	-0.926	3.014	-0.659	-0.517
	(1.227)	(2.270)	(1.184)	(2.215)
Prenatal exposure to TSPs$\times I_{2000}$	-0.326	3.187	-0.429	-0.910
	(1.331)	(2.505)	(1.357)	(2.444)
Prenatal exposure to TSPs$\times I_{2001}$	-1.053	2.824	-1.603	-1.823
	(1.780)	(3.030)	(1.739)	(2.955)
Prenatal exposure to TSPs$\times I_{2002}$	-0.226	2.921	-0.619	-0.957
	(2.260)	(3.017)	(1.866)	(2.943)
Gender(girl=1)	-0.056	-0.037	0.135**	0.167***
	(0.066)	(0.065)	(0.065)	(0.064)
Birth Year Fixed Effect	Y	Y	Y	Y
Birth City Fixed Effect	Y	Y	Y	Y
N	843	843	843	843
Adjusted-R2	0.163	0.143	0.165	0.140

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings and birth order. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 4: Test scores and prenatal exposure to TSPs: air pollution of multiple years

	(1) OLS Math	(2) OLS Math	(3) OLS Math	(4) OLS Math	(5) OLS Language	(6) OLS Language	(7) OLS Language	(8) OLS Language
Prenatal exposure to TSPs	-4.397***	-4.714***	-5.186***	-5.360***	-2.460**	-2.385**	-2.906**	-2.922**
	(1.162)	(1.159)	(1.272)	(1.332)	(1.012)	(1.060)	(1.217)	(1.280)
$TSPs_{t+1}$	0.637	1.459	1.613	1.465	-1.997	-2.194	-2.024	-2.037
	(1.392)	(1.484)	(1.468)	(1.428)	(1.271)	(1.377)	(1.377)	(1.365)
$TSPs_{t+2}$		-1.420	-0.836	-0.929		0.340	0.986	0.978
		(1.167)	(1.301)	(1.348)		(1.091)	(1.312)	(1.300)
$TSPs_{t+3}$			-1.236	-0.520			-1.368	-1.304
			(1.675)	(1.681)			(1.729)	(1.683)
$TSPs_{t+4}$				-1.099				-0.099
				(1.514)				(1.329)
Gender(girl=1)	-0.030	-0.031	-0.030	-0.027	0.194**	0.195**	0.196**	0.196**
	(0.082)	(0.082)	(0.082)	(0.083)	(0.082)	(0.082)	(0.082)	(0.083)
$\sum TSPs$	-3.760***	-4.674***	-5.645***	-6.443**	-4.458***	-4.239***	-5.312***	-5.384**
	(1.197)	(1.430)	(2.006)	(2.504)	(1.078)	(1.373)	(1.884)	(2.292)
Birth Year Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Birth City Fixed Effect	Y	Y	Y	Y	Y	Y	Y	Y
N	604	604	604	604	604	604	604	604
Adjusted-R2	0.127	0.127	0.126	0.126	0.120	0.119	0.118	0.117

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings and birth order. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 5: Cognitive effect of exposure to TSPs before birth and prenatal exposure to TSPs

	(1) OLS Math	(2) OLS Language	(3) OLS Math	(4) OLS Language
Prenatal exposure to TSPs	-2.403**	-1.598*	-1.965*	-1.127
	(1.039)	(0.880)	(1.077)	(0.943)
$TSPs_{t-1}$	0.111	-0.298	-0.049	-0.500
	(0.862)	(0.903)	(0.936)	(0.826)
Accumulative exposure to TSPs after birth			-0.161**	-0.117*
			(0.081)	(0.069)
$TSPs_t + TSPs_{t-1}$	-2.292***	-1.887***	-2.014**	-1.627*
	(0.712)	(0.602)	(0.827)	(0.858)
Gender(girl=1)	-0.038	0.152**	-0.060	0.148**
	(0.064)	(0.069)	(0.068)	(0.066)
Birth Year Fixed Effect	Y	Y	Y	Y
Birth City Fixed Effect	Y	Y	Y	Y
N	837	837	803	803
Adjusted-R2	0.112	0.105	0.086	0.085

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings and birth order. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 6: Prenatal exposure to TSPs and current height, weight, and health status

	(1) OLS Current height	(2) OLS Current weight	(3) OLS "Poor" health
Prenatal exposure to TSPs	-0.010	0.201	1.654**
	(0.038)	(0.135)	(0.774)
Accumulative exposure to TSPs after birth	-0.011**	-0.034*	-0.076
	(0.005)	(0.017)	(0.101)
Gender(girl=1)	-0.003	-0.009	0.190***
	(0.003)	(0.014)	(0.063)
Birth City Fixed Effect	Y	Y	Y
N	1176	1176	1176
Adjusted-R2	0.042	0.065	0.067

Notes: Heath status is self-evaluated by a question: "What is your current health status compared with your peers at the same age?" The answer has five categories: "1. Excellent", "2. Good", "3. Average", "4. Poor", and "5. Very Poor". There are very few responses for "Poor" and "Very Poor", so I group the last three into one group representing "Poor health". Current weight and height are weighted by the national average height by age and gender. I control the number of siblings and birth order in these estimations. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 7: Multiple measures of air pollution and test scores

	(1) OLS Math	(2) OLS Language	(3) OLS Math	(4) OLS Language	(5) OLS Math	(6) OLS Language	(7) OLS Math	(8) OLS Language
Prenatal exposure to SO2	2.078	1.107			-0.150	0.168	3.081	0.638
	(2.939)	(2.621)			(3.231)	(2.914)	(3.385)	(3.205)
Prenatal exposure to Nox			3.424	1.780	4.554*	2.485	3.997	2.052
			(2.323)	(2.279)	(2.432)	(2.423)	(2.492)	(2.518)
Prenatal exposure to TSPs					-2.092**	-1.672**	-2.175**	-1.945**
					(0.843)	(0.670)	(0.870)	(0.923)
Accumualtive exposure to SO2 after birth							-0.881	-0.226
							(0.606)	(0.671)
Accumualtive exposure to NOx after birth							0.001	0.027
							(0.115)	(0.125)
Accumualtive exposure to TSPs after birth							0.218	-0.215
							(0.296)	(0.326)
Gender(girl=1)	-0.018	0.180***	-0.037	0.172**	-0.047	0.174**	-0.079	0.170**
	(0.064)	(0.067)	(0.064)	(0.066)	(0.065)	(0.068)	(0.070)	(0.070)
Birth City Fiexed Effect	Y	Y	Y	Y	Y	Y	Y	Y
Birth Year Fixed Effect	Y	Y	Y	Y	Y	Y	N	N
N	874	874	838	838	810	810	776	776
Adjusted-R2	0.104	0.102	0.104	0.105	0.101	0.107	0.075	0.090

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings and birth order. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 8: Prenatal exposure to TSPs and test scores, migrants and urban nonmovers

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	OLS	OLS
	Migrants only Math	Migrants only Language	ALL Math	ALL Language	ALL Math	ALL Language
Prenatal exposure to TSPs	-3.838***	-3.635*	-2.539***	-1.977***	-2.520***	-1.666***
	(1.306)	(2.005)	(0.552)	(0.576)	(0.585)	(0.591)
Inverse Mills Ratio					-0.519***	-0.419***
					(0.145)	(0.144)
Birth Year Fixed Effect	Y	Y	Y	Y	Y	Y
Birth City Fixed Effect	Y	Y	Y	Y	Y	Y
N	161	161	970	970	881	881
Adjusted-R2	0.113	0.201	0.061	0.093	0.085	0.119
	(7)	(8)	(9)	(10)	(11)	(12)
	OLS	OLS	OLS	OLS	OLS	OLS
	Migrants only Math	Migrants only Language	ALL Math	ALL Language	ALL Math	ALL Language
Prenatal exposure to TSPs	-3.730***	-2.740*	-1.725**	-1.662***	-1.544**	-1.485**
	(1.336)	(1.509)	(0.662)	(0.628)	(0.676)	(0.630)
actspmg2	0.181	0.037	-0.056	-0.019	-0.047	-0.011
	(0.152)	(0.141)	(0.062)	(0.060)	(0.059)	(0.055)
Inverse Mills Ratio					-0.482***	-0.444***
					(0.142)	(0.136)
Birth Year Fixed Effect	N	N	N	N	N	N
Birth City Fixed Effect	Y	Y	Y	Y	Y	Y
N	172	172	1015	1015	920	920
Adjusted-R2	0.175	0.237	0.077	0.095	0.100	0.119

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings, birth order and gender. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level. The first stage used for calculating inverse mills ration is reported in the appendix.

Table 8 continued: Prenatal exposure to TSPs and test scores, migrants and urban nonmovers

	(13)	(14)	(15)	(16)	(17)	(18)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Migrants only Math	Migrants only Language	ALL Math	ALL Language	ALL Math	ALL Language
Prenatal exposure to TSPs	-0.903	-5.612*	-1.776	-5.121**	-2.283	-4.366*
	(2.973)	(3.299)	(2.021)	(2.235)	(2.031)	(2.228)
Inverse Mills Ratio					-0.482***	-0.446***
					(0.137)	(0.131)
Birth Year Fixed Effect	Y	Y	Y	Y	Y	Y
Birth City Fixed Effect	Y	Y	Y	Y	Y	Y
N	172	172	1015	1015	920	920
Adjusted-R2	0.096	0.228	0.076	0.074	0.100	0.103

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings, birth order and gender. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level. The first stage used for calculating inverse mills ration is reported in the appendix.

Table 9: Prenatal exposure to TSPs and cognitive development: households at different income levels

	(1) OLS Math	(2) OLS Language
Prenatal exposure to TSPs	-2.468**	-1.844**
	(0.972)	(0.900)
Prenatal exposure to TSPs×**1 (household income ranks between 33% and 66%)**	0.831	0.539
	(0.980)	(1.103)
Prenatal exposure to TSPs×**1 (household income ranks between 67% and 100%)**	0.842	0.041
	(0.890)	(1.092)
Accumulative exposure to TSPs after birth	-0.104	-0.087
	(0.090)	(0.082)
Accumulative exposure to TSPs after birth×**1 (household income ranks between 33% and 66%)**	-0.079	-0.040
	(0.092)	(0.095)
Accumulative exposure to TSPs after birth×**1 (household income ranks between 67% and 100%)**	-0.091	0.003
	(0.080)	(0.093)
Gender(girl=1)	-0.069	0.157**
	(0.068)	(0.068)
Birth City Fixed Effect	Y	Y
Birth Year Fixed Effect	N	N
N	809	809
Adjusted-R2	0.081	0.091

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings and birth order. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table 10: Prenatal exposure to TSPs and test scores, by the season of birth

	(1) OLS Math	(2) OLS Language
Prenatal exposure to TSPs	-1.811**	-1.891**
	(0.816)	(0.817)
Prenatal exposure to TSPs×**Birth Season 2** (**APR – JUN**)	-1.103	0.069
	(1.055)	(1.102)
Prenatal exposure to TSPs×**Birth Season 1** (**JUL – SEP**)	0.451	0.977
	(1.086)	(1.019)
Prenatal exposure to TSPs×**Birth Season 1** (**OCT – DEC**)	-1.182	-1.352*
	(0.752)	(0.747)
Birth Year Fixed Effect	Y	Y
Birth City Fixed Effect	Y	Y
Birth Season Fixed Effect	Y	Y
N	843	843
Adjusted-R2	0.096	0.106

Notes: The whole twelve months are categorized into four seasons: season 1 (JAN-MAR), season 2 (APR-JUN), season 3 (JUL-SEP), and season 4 (OCT-DEC). For those kids who were born in the fourth season (i.e., Oct-Dec), the mother's pregnancy starts between December and February in the previous year, or the last winter period. All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings, birth order and gender. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

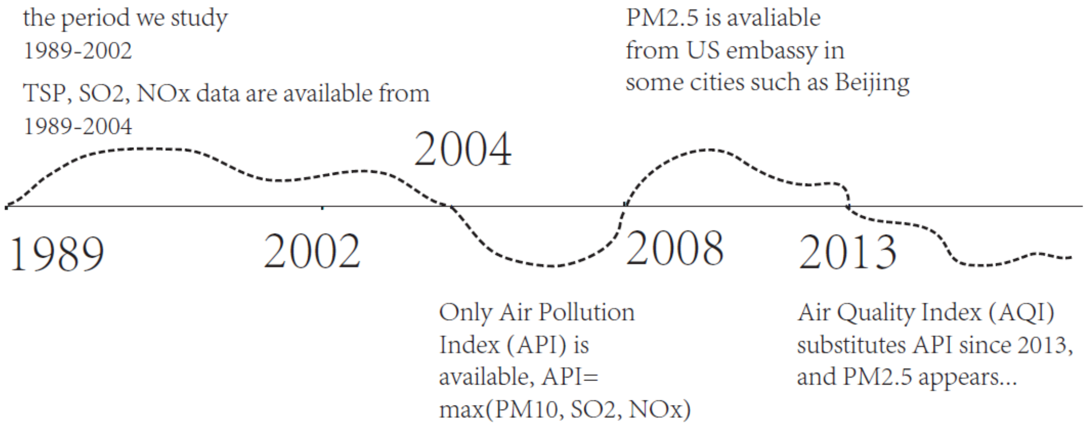

Figure 1: Data availability of air pollution in China

Figure 2: Cities in this study

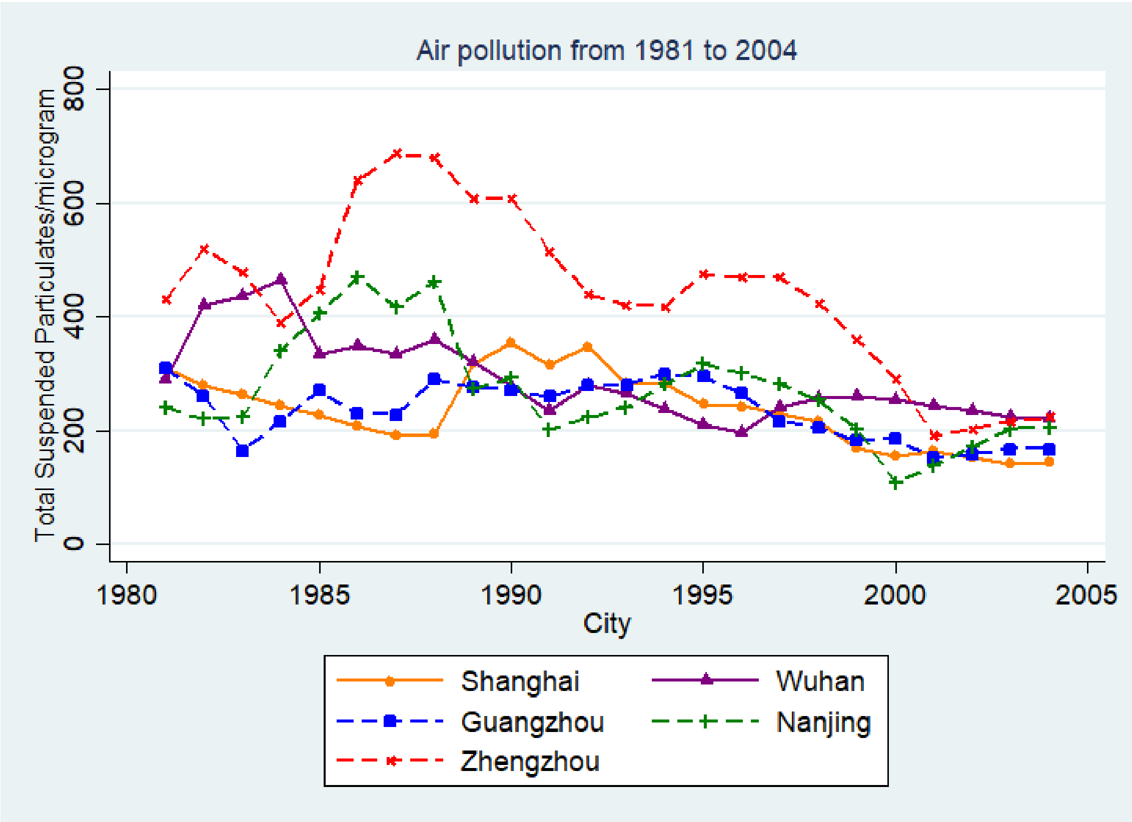

Figure 3: Annual daily average TSP of selected cities
Data Source: World Bank and Chinese Environment Yearbooks

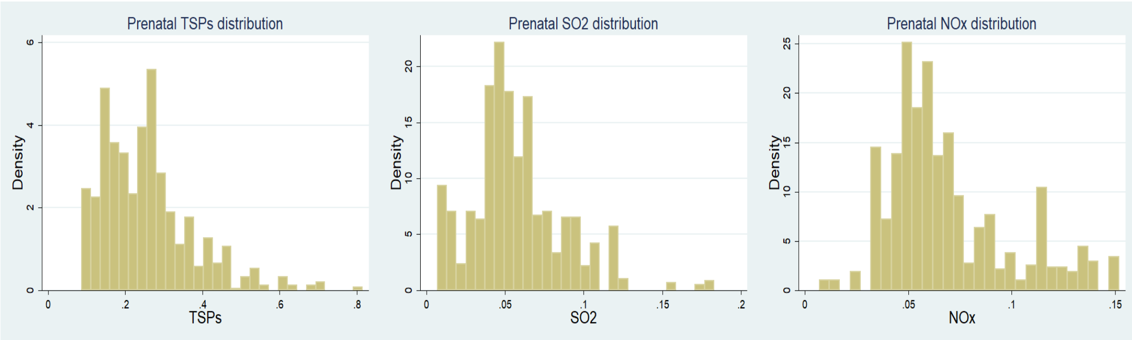

Figure 4: Distribution of various air pollutants (total suspended particulates, SO2, and NOx)

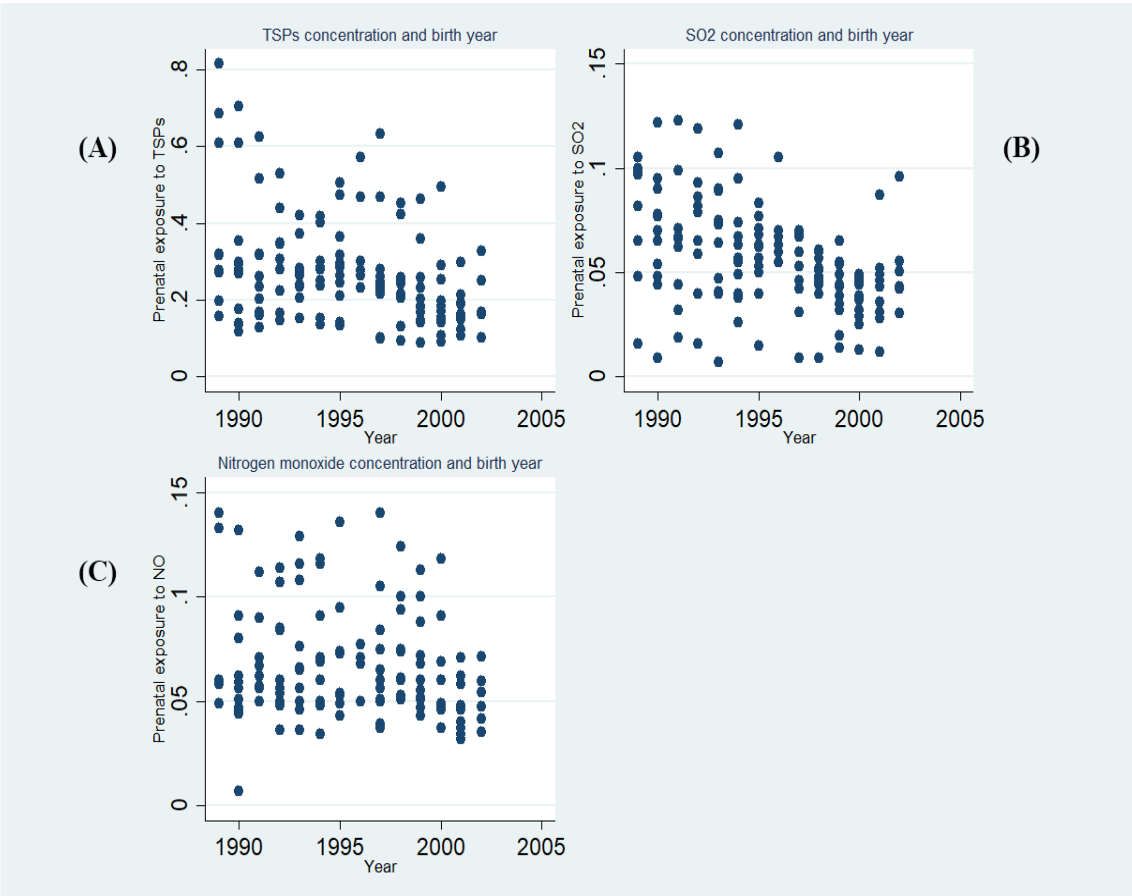

Figure 5: Prenatal exposure to TSPs, SO2, and NOx by birth years

Notes: (A) Concentration of prenatal exposure to TSPs; (B) Concentration of prenatal exposure to SO2; (C) Concentrations of prenatal exposure to NOx.

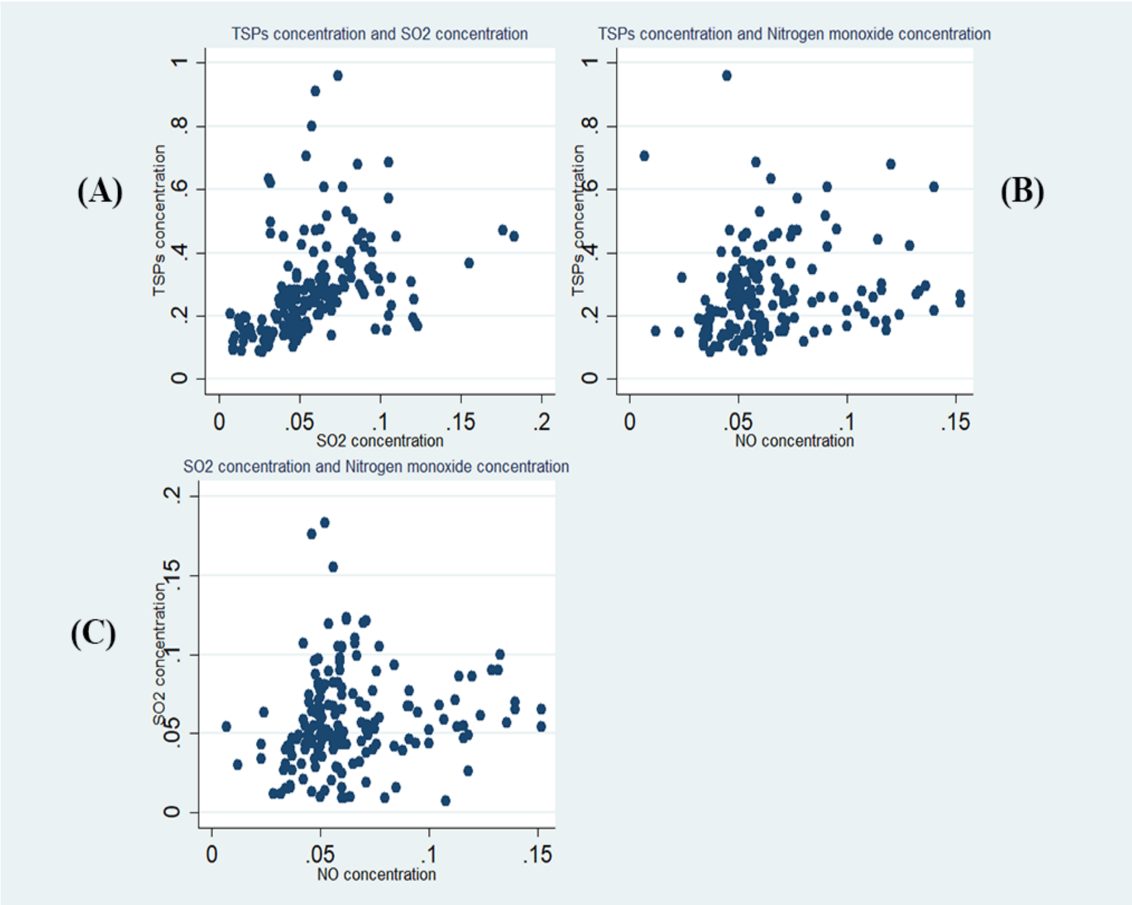

Figure 6: Correlation of different air pollutants including TSPs, SO2, and NOx.

Notes: (A) Prenatal exposure to TSPs and SO2; (B) Prenatal exposure to TSPs and NOx; (C) Prenatal exposure to SO2 and NOx.

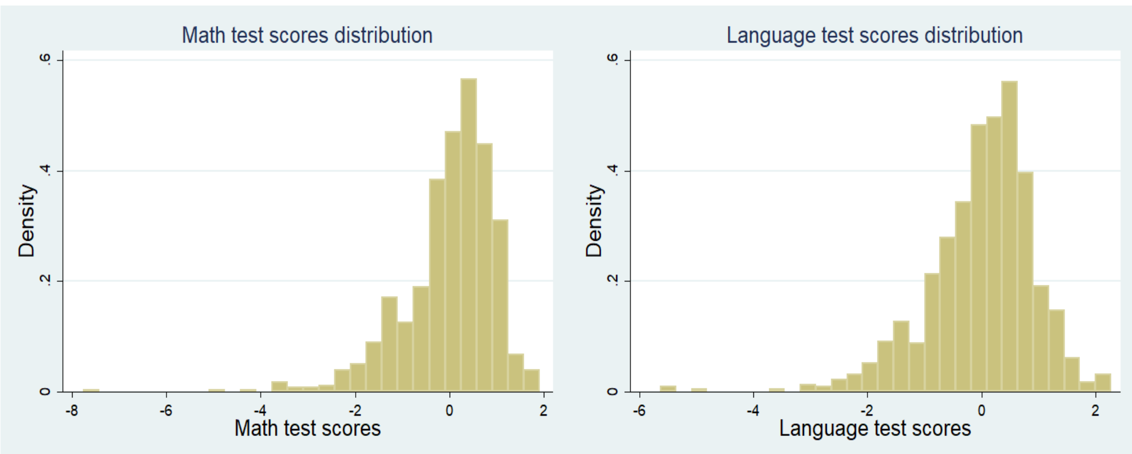

Figure 7: Distribution of standardized scores of math exam and language exam

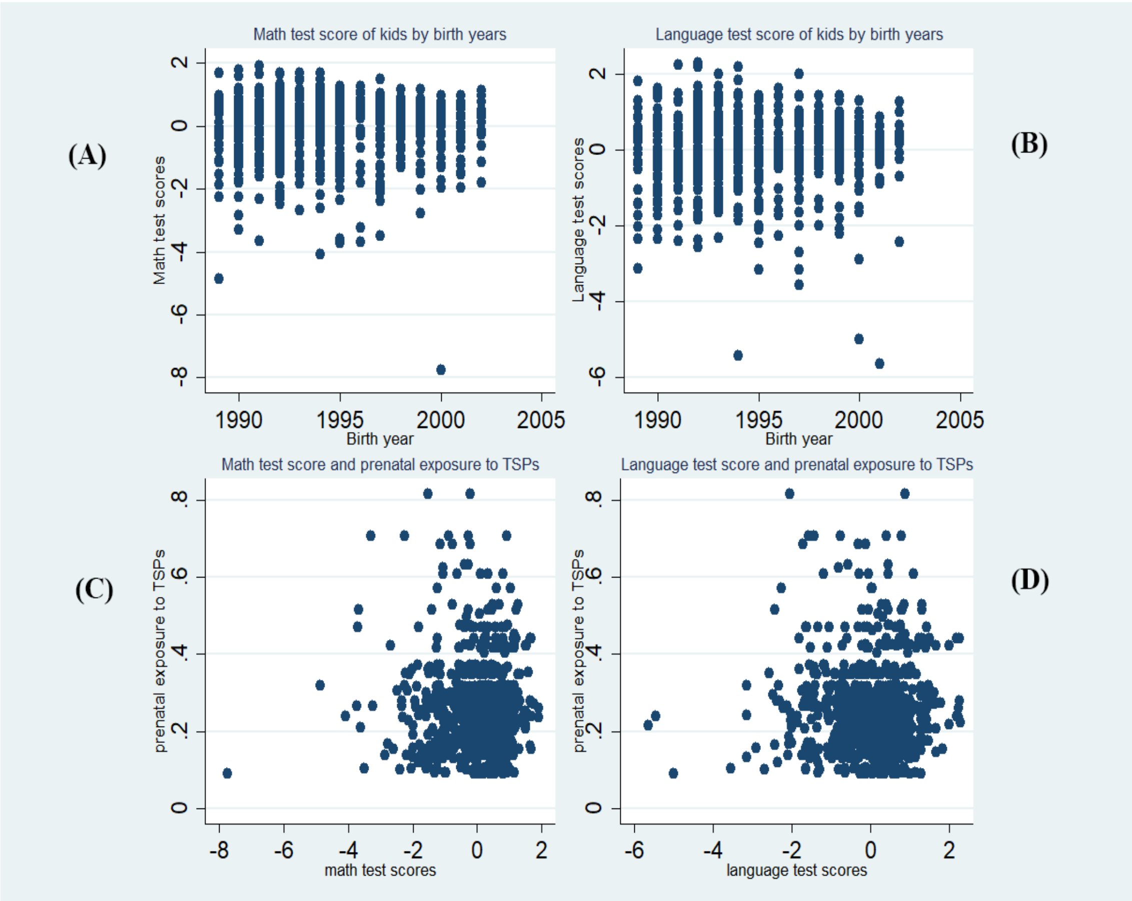

Figure 8: Distribution of test scores by birth years and test scores against prenatal exposure to TSPs

Notes: (A) Math test scores of students by the birth year; (B) Language test scores of students by the birth year; (C) Prenatal exposure to TSPs and math test scores; (D) Prenatal exposure to TSPs and language test scores.

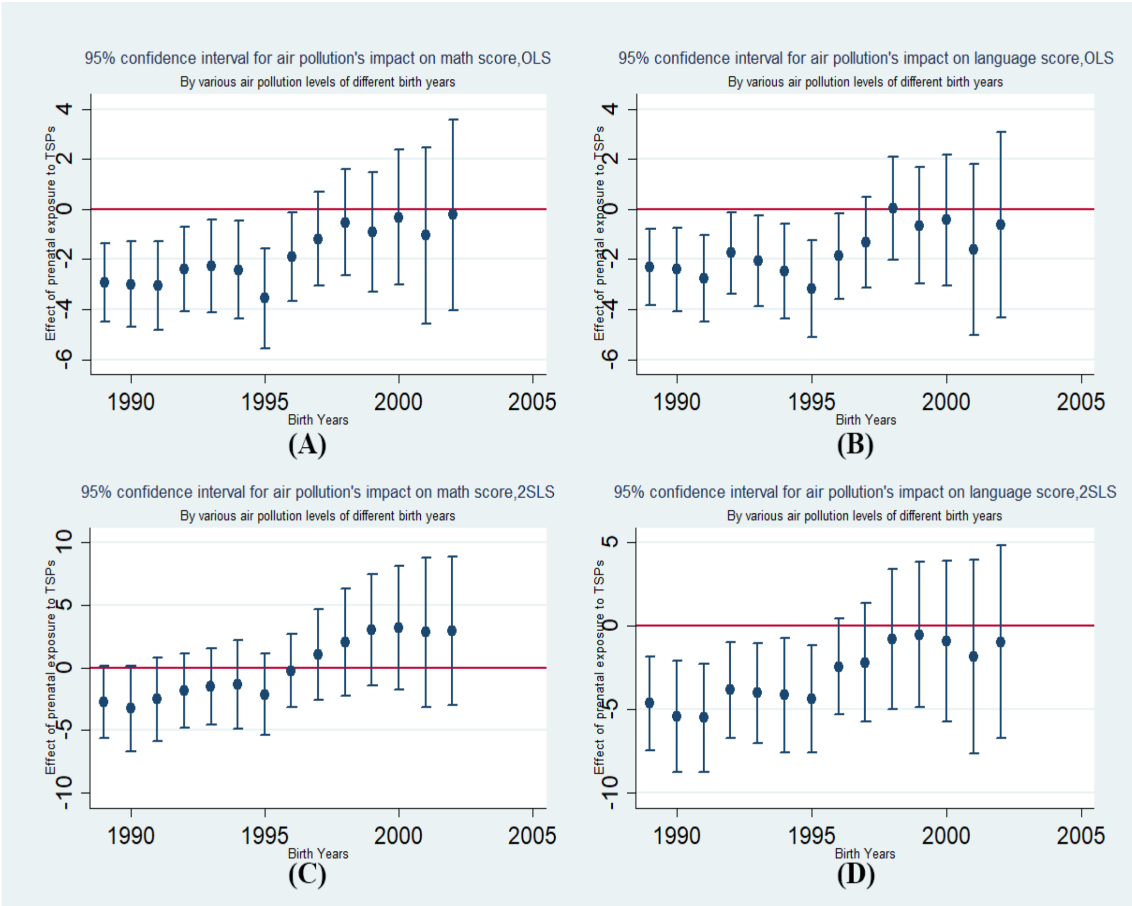

Figure 9: 95% confidence interval of the estimated effect of prenatal exposure to TSPs on test scores

Notes: (A) Cognitive effect of prenatal exposure to TSPs on math test scores, OLS; (B) Cognitive effect of prenatal exposure to TSPs on language test scores, OLS; (C) Cognitive effect of prenatal exposure to TSPs on math test scores, 2SLS; (D) Cognitive effect of prenatal exposure to TSPs on language test scores, 2SLS.

Appendix

Table A1: First stage results of 2SLS in Table 1

VARIABLES	Prenatal exposure to TSPs
Number of days with precipitation above 0.1cm	-0.001***
	(0.000)
Average temperature	-0.008*
	(0.004)
Humidity (%)	0.010***
	(0.001)
Annual sunshine hours	0.000***
	(0.000)
Instrumental Variables	
Wind Speed (m/s)	-0.047***
	(0.009)
Atmospheric pressure (hPa)	0.007***
	(0.001)
Weak IV TEST	35.276***
Underidentification Test	69.762***
Overidentification Test	2.415
Observations	843
R-squared	0.852

Notes: These regressors are included in the estimation above, but their coefficients are not reported in this table: school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings, birth order and gender, birth city fixed effect and birth year fixed effect. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level. Cragg-Donald Statistics is used to test the null hypothesis of weak instrumental variables, a rejection of the null hypothesis indicates the instruments are not weak. Anderson canon. corr. LM statistic is for the under-identification test. A rejection of the null hypothesis indicates full rank and there is no under-identification issue. Sargan Statistics is used for over-identification test, the null hypothesis is that all instruments are valid IVs. Failing to reject the null hypothesis indicates no over-identification issue.

Table A2: Two-stage least squares estimation with accumulative exposure to TSPs

	(1) OLS Math	(2) OLS Language
Prenatal exposure to TSPs	-2.364	-6.309*
	(4.042)	(3.708)
Accumulative exposure to TSPs after birth	-0.148	0.035
	(0.162)	(0.150)
Gender(girl=1)	-0.067	0.156**
	(0.064)	(0.067)
Birth City Fixed Effect	Y	Y
N	809	809
Adjusted-R2	0.088	0.042

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings and birth order. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table A3: Heckman selection function of parent's migration

	(1) Porbit Migrant=1
Father is Hanzu	-1.183*
	(0.674)
Mother is Hanzu	1.016
	(0.706)
Number of father's siblings	0.016
	(0.037)
Number of mother's siblings	0.081**
	(0.035)
Father is remarried	-1.106***
	(0.349)
Mother is remarried	1.184***
	(0.354)
How many kids that father has	0.357*
	(0.196)
how many kids that mother has	0.293
	(0.193)
Father's birth order	Y
Mother's birth order	Y
N	1354
Adjusted-R2	0.128

Notes: Error terms are double clustered by birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table A4: Impacts of prenatal exposure to TSPs on test scores, by school levels and by genders

	(1) OLS Primary School Math	(2) OLS Secondary School Math	(3) OLS Primary School Language	(4) OLS Secondary School Language
Prenatal exposure to TSPs	-0.904	-4.171***	-0.246	-3.169***
	(1.161)	(0.912)	(1.044)	(0.855)
Accumulative exposure to TSPs after birth	-0.052	-0.032	-0.250*	0.099
	(0.165)	(0.116)	(0.131)	(0.133)
Gender(girl=1)	-0.171*	-0.047	0.155*	0.208**
	(0.098)	(0.088)	(0.089)	(0.088)
N	352	457	352	457
Adjusted-R2	0.224	0.097	0.180	0.115
	(1) OLS Girls Math	(2) OLS Boys Math	(3) OLS Girls Language	(4) OLS Boys Language
Prenatal exposure to TSPs	-1.488	-1.717*	-1.494*	-1.810*
	(0.926)	(0.926)	(0.843)	(0.980)
Accumulative exposure to TSPs after birth	-0.105	0.025	-0.125*	0.100
	(0.081)	(0.090)	(0.073)	(0.089)
N	391	418	391	418
Adjusted-R2	0.091	0.114	0.121	0.090

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings and birth order. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table A5: Test scores and exposures to TSPs around the birth year

	(1) OLS Math	(2) OLS Math	(3) OLS Math	(4) OLS Language	(5) OLS Language	(6) OLS Language
TSPs in the birth year	-2.403**	-2.786**	-2.705*	-1.598*	-0.915	-0.551
	(1.039)	(1.087)	(1.404)	(0.880)	(0.935)	(1.274)
TSPs in the year before birth	0.111		-0.058	-0.298		-0.561
	(0.862)		(0.891)	(0.903)		(0.963)
TSPs in the year after birth		0.633	0.477		-1.226	-1.148
		(1.192)	(1.234)		(1.000)	(1.049)
sum(tsps)	-2.292***	-2.153**	-2.286**	-1.895***	-2.141***	-2.260***
	(0.712)	(0.903)	(0.932)	(0.605)	(0.742)	(0.808)
Birth Year Fixed Effect	Y	Y	Y	Y	Y	Y
Birth City Fixed Effect	Y	Y	Y	Y	Y	Y
N	837	804	798	837	804	798
Adjusted-R2	0.112	0.103	0.102	0.105	0.107	0.102

Notes: All estimations above control school quality and type, school grade fixed effects, expenditure on tutoring classes, family characteristics including parent's education, income, and children's siblings, birth order and gender. I also control cities' GDP per capita in the birth year and test year (2008), and the weather in the birth year and test year. Error terms are double clustered by the birth city and birth year. Standard errors are reported in parentheses. *** indicates significance at the 1% level., ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Table A6: Data summary of migrant's children

	Observation	Mean	S.D.	Min	Max
z-score math	172	0.049	0.995	-3.946	1.309
z-score language	172	0.083	0.975	-4.074	1.777
Prenatal exposure to TSPs (mg=1000 μg)	172	0.263	0.117	0.103	0.705
Accumulative exposure of TSPs after birth	161	2.760	1.403	0.832	7.582
Gender (Girls=1)	172	0.547	0.499	0	1
Ln (Father's annual income)	172	7.460	1.029	0	9.798
Ln (Mother's annual income)	172	6.227	2.703	0	9.210
Father's years of education	172	8.215	2.134	2	12
Mother's years of education	172	7.035	2.296	1	12
Number of siblings	172	1.285	0.567	1	3
Birth order	172	1.564	0.694	1	4
Attending average school	172	0.657	0.476	0	1
Attending better than average school	172	0.279	0.450	0	1
Attending worse than average school	172	0.012	0.108	0	1
Attending best school	172	0.052	0.223	0	1
Attending public School	172	0.744	0.438	0	1
Attending private School	172	0.174	0.381	0	1
Attending boarding school	172	1.866	0.341	1	2
Expenditure on tutoring classes	172	100.082	456.491	0	5000
Birth year	172	1996.384	3.434	1989	2002

Source: China household Income Project 2008, migrant's sample; World Bank's Development Economics Research Group (DECRG), China Environmental Yearbooks.