Air Pollution and Academic Performance: Evidence from China

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Abstract

This paper studies the relationship between air pollution at birth and youth cognitive skill development in China. This study combines the air pollution data by location compiled by the World Bank with the Chinese Household Income Project (CHIP) 2008. OLS and 2SLS results show that a standard deviation (120 microgram/m^3) increase of total suspended particulate at birth lowers the average literature score by 2.16 to 2.52 percent, and it lowers the average math score by 2.76 to 5.28 percent. The detrimental impact of early exposure to air pollution becomes more apparent as the child ages. Air pollution exposure in utero has a greater adverse impact than does exposure to air pollution in later childhood.

Key Word: Air Pollution, Cognitive Skills, Human Capital, China, Children

JEL: I18, I21, Q51, Q53

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1. Introduction

Air pollution is commonly associated with adverse health conditions. Evidence suggests that children are particularly vulnerable to ambient pollutants. High air pollution leads to more physical and mental problems for children (Evans, 2003; Gauderman et al., 2002; Romieu et al., 1996). However, few studies have measured the detrimental impact of air pollution on youth cognitive ability and academic performance. Since Chinese air quality is notoriously poor, a natural question is "what is the impact of air pollution on academic performance in China? ". While air pollution is a consequence of the economic development of China, pollution could also hinder future development if it lowers the cognitive potential of the next generation.

Early life shocks can have both immediate and growing persistent adverse impacts on life outcomes. Almond and Currie (2011) document the development of this 'fetal origins' theory. Barker (1990) was the first to argue that adverse conditions as early as conception might lead to future diseases. Since then, many epidemiology studies find that the adverse events in utero have a negative impact on neonatal health[1]. Currie and Hyson (1999) studied the effect of low birthweight on economic success in adulthood. Since then, air pollution in utero has been associated with various children's health consequences including asthma (McConnell, et al 2002), infant mortality (Chay and Greenstone, 2003a, 2003b; 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).

Health early in life has been tied to cognitive development and brain function (Figlio, 2014; Case and Paxson, 2008; Case and Paxson, 2009; Currie et al., 2010). Kremer and Miguel (2004) found that early treatment for intestinal worms improved children's health and reduced absenteeism in schools. Baird *et al* (2011) showed that as adults, those getting early deworming treatments worked more hours and earned 20% higher wages. Maluccio et al (2009) found that early childhood nutritional intervention improved reading and non-verbal cognitive ability and raised adult earnings for both

[1] See Barker (1995), Gluckman and Hanson (2009), Secki (1997), Eriksson (2001), Hanson and Gluckman (2014)

women and men. Early exposure to air pollutants could also affect cognitive ability and impede human capital formation. Only a few studies have examined the long-run impact of air pollution on human capital formation (Sanders, 2011; Bharadwaj et al, 2017), and even less is known about the mechanisms behind these adverse impacts. There are at least three ways air pollution could affect academic performance: (1) air pollution could affect metabolism and brain development; (2) air pollution could cause attention problems when attending school and doing homework; and (3) air pollution could lead to school absenteeism due to sickness.

The purpose of this paper is to explore the long-term relationship between air pollution and youth academic performance in China. This study uses linked data on Chinese regional air pollution during 1981-2004 compiled by the World Bank and information from two household surveys conducted in 2008 and 2012 to show how total suspended particulates (TSP) at birth affect children's later academic performance and cognitive skills. The Chinese Household Income Project (CHIP) 2008 contains the information of individual students for fourteen cities of nine provinces in China. It includes the academic performance in Math and Literature for individual students. China Family Panel Studies (CFPS) 2012 surveys the households across twenty-five provinces in China. It provides the scores of two standardized tests evaluating Math ability and Literacy for different ages. In this paper, I match the air pollution with the sample of CHIP 2008 based on the city codes, and connect the air pollution with CHPS 2012 on provincial level. Our estimates control for other possible confounding effects of household characteristics, school features, economic demographics and city fixed effects. Ordinary Least Square (OLS) estimation and Instrumental Variable (IV) estimation are used to test three hypothesis derived from a theoretical model built on Currie et al. (2010). This study finds that the air pollution at birth has a significant detrimental impact on youth cognitive skill development. The impact of early health shock on human capital becomes more apparent as the child ages. The early health shock also has a greater impact than late shocks on human capital outcomes since early shocks accumulate through time. OLS result shows that a one standard deviation (120 $\mu g/m^3$) increase in total suspended particulates (TSP) will lower the literature score by 2.16 to 2.52 percent, and it will lower the math score by 2.76 to 3.48 percent.

This research contributes to the literature in three aspects. First, it adds to the current literature about the long-run adverse impact of air pollution on academic performance (Sanders, 2012; Bharadwaj et al., 2017; Reyes, 2011). By using detailed survey data, this paper provides the micro-foundations supporting the “fetus origin” hypothesis, controlling for heterogeneity at the individual student level. This study finds that air pollution at birth has a significantly negative effect on student’s cognitive development.

Second, this is among the first studies examining the long-term correlation between air pollution and cognitive development in China. The only similar work is Zhang et al. (2018) who measure the short-run impact of air pollution on cognitive development[2]. If the negative effects they find are temporary, the consequences for future quality of life and economic development may not be great. However, if damage to cognitive potential and academic performance persists over the lifetime, these external costs will lower potential for individual welfare and future economic growth due to human capital loss.

Third, this study sheds light on the importance of reducing air pollution from the perspective of human capital accumulation. The severe air pollution in developing countries not only reduces present productivity, but also dampens future economic growth.

This paper proceeds as follows. Section 2 provides background on Chinese air pollution and reviews previous studies of 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 model and empirical specifications. Section 5 presents the empirical results. I discuss in section 6 and give concluding remarks in section 7.

[2] Zhang and Chen (2017) conducted a panel study by linking the CFPS 2010 and CFPS 2014 with the air pollution indexes (API) provided by Chinese Environment Department. Their research focuses on the contemporaneous impact of air pollution on the cognitive skill development across ages. They found a one standard deviation increase in API within a week lowers the test score by 1.6 percent, and it lowers the math score by 0.6 percent.

2. Background

2.1 Chinese air pollution

China is notorious for its poor air quality. 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 caused both economic and non-economic damages. Zhang et al. (2008) estimated that the total economic cost in China caused by PM_{10}[3] was approximately $30 billion in 2004. 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 level of $PM_{2.5}$[4] in Beijing was 155 $\mu g/m^3$ in the winter of 2016[5], about 16 times the WHO standard.

2.2 Air pollution, brain functioning and cognitive ability development

Most research on the health consequences of air pollution are from epidemiology. Air pollution brings direct brain damage through respiratory system, leading to more inflammation and depressing the neurons and white matter cells. (Calderon-Garciduenas et al., 2002; Costa et al., 2014; Fonken et al., 2003). Air pollution also affects genetic expression which controls brain function (Risom et al., 2005; Calderon-Garciduenas et al., 2003). Perera et al. (2009) found that prenatal exposure to polycyclic aromatic hydrocarbons (PAH) significantly lowers children's IQ at age 5 in New York. The previous study found that fetal exposure to air pollution does not significantly alters birth weight (Perera et al., 2009).

Most economic research focuses on the contemporaneous impact of air pollution on youth cognitive ability and academic performance. For example, Zweig et al.(2009) found a negative short-term relationship between air pollution caused by fuel-combustion and test scores in California. Lavy et al. (2014) found a detrimental impact of air pollutants (PM2.5 and CO) on students' academic performance in Israel.

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[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.

[5] Data Source: Air quality data of U.S. embassy in Beijing, China.

3. Data

This study combines several data sources to evaluate the effect of air pollution on academic performance and cognitive ability. This section describes how this research links the air pollution data to children who are born between 1989 and 2004.

3.1 Air pollution

The World Bank's Development Economics Research Group (DECRG) collaborated with the China National Environmental Monitoring Stations to provide Chinese air pollution data from 1981 to 1995. The China *Environmental Yearbooks* provides similar data from 1990 to 2005. I combine these two series for our measure of air pollution. For overlapping years, I checked for consistency and addressed any disagreements in values. The resulting harmonized data set includes air pollution data for 90 major Chinese cities from 1981 to 2004. Three concentrations of air pollutants were collected: Total Suspended Particulates (TSPs), Sulfur Dioxide (SO_2) and Nitrous Oxide (NO_x).

Figure 1 shows the pollution map of major cities in 1990, 1995 and 2000 provided by DECRG. Severe air pollution exists in all areas of China. Air pollution in the North and Southwest is much more severe than in South China. The air quality improves in most cities while the air pollution is still a problem. Although Chinese government data on air pollution may be suspect (Ghanem & Zhang, 2014), Chen, Ebenstein, Greenstone and Li (2013), who used the 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 in this study using an instrumental variable estimation method to correct for the potential measurement error problem and compare the empirical results to ordinary least-squares estimation.

Figure 2 shows the time series data on total suspended particulates for a subsample of 7 Chinese cities. The air pollution is particularly severe at the beginning of 1980s. The suspended particulates are atmospheric particulate matter (PM) that have a diameter of less than 100 micrometers, which contains large particles like pollens and finer matters produced by industry and fuel combustion. Air quality improved during the 1990s and then stayed relatively constant at 100-250 $\mu g/m^3$ since 2000. Table 1.3 lists the statistical description of air pollution. The average total suspended particulates at birth is around 260 $\mu g/m^3$, which is very high compared with the WHO standard of total suspended particulates.

3.2 Test scores and household demographics

Individual test scores were obtained from two surveys, the 2009 Chinese Household Income Project (CHIP), and the 2012 China Family Panel Study (CFPS). For both datasets, I only study the sample from urban area since air pollution monitors are mainly located in cities. Both datasets contain detailed household demographics including parents' information, children's characteristics and schools' features. The CHIP data contains scores on exams of Chinese literature and mathematics at different grades of the students of fourteen cities in nine provinces. This dataset contains the city code so that it can be matched with the air pollution data. The CFPS includes test scores of two standardized tests, a word test and a math test. Due to confidentiality requirements, the CFPS only identifies individuals by provinces. The CFPS 2012 covers individual students in twenty-five provinces. Since the air pollution data is at the city-level, this study cannot perfectly match the air pollution data to household data. As a result, I aggregate the pollution data to the province level for the CFPS urban sample. The study focuses on children aged 6 to 19 who are in the primary school, middle school and high school. To avoid misusing pollution exposure due to migration (Banzhaf and Walsh, 2008), I only includes urban non-movers in this study.

Tables 1 describes the data in this study. Information on children includes age, gender, age entering school, birthweight, weight and height. The education related factors are school type, school quality, grade, distance between school and home, and education expenditure. Other household characteristics include parents' education, annual income, and the number of children. In addition, parents' word test scores and math test scores are available in the CFPS 2012.

3.3 Other factors

Weather can be a confounding factor because of the correlation between temperature, rainfall, and wind with air pollution levels. To isolate the impact of air pollution from other weather factors, I include the weather data of the cities when using CHIP in this study[6]. The weather data is from GSOD (Global Summary of the Day), NOAA (National Centers for Environmental Information). The annual mean value of temperature, wind speed and total heating degree hours (degree lowers than $T_{cutoff} = 65F^{\circ}/18.3C^{\circ}$) for each city are included in our analysis. Table 1 describes the weather measures during the period of our study.

In the empirical analysis, I adopt Sanders' (2012) strategy of using employment share in the manufacturing sector as an instrumental variable for air pollution. He found the employment share of manufacturing sector is highly correlated with local air pollution. The manufacturing industries produce tons of dust and gas, which contribute to the severe air pollution in Texas during 1980s. This study also includes economic demographics such as GDP per capita at the birth and test time 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 and province between 1989 and 2004. Table 1 contains the description of these factors. The GDP per capita at birth is 11636 CNY and 56520 CNY at test date after adjusting for inflation.

To examine whether air pollution affects physical health, I test the relationships between air pollution and youth maturity including birthweight, height and weight. The height and weight is normed with the national average of youth in urban areas by different ages and genders. The national average height and weight are from the Yearbook of Health in China 2016, published by National Health Commission of China. It includes urban youth height and weight by genders from age seven to age nineteen.

After I match air pollution data with the household data, I have information about the students themselves, their households' characteristic, the air pollution level at their birth, and other features including the quality of schools.

[6] The CFPS can only be used on the provincial level, we do not include the provincial average of weather variables in the analysis when using CFPS 2012.

4. Conceptual Framework

Early shocks to fetal health can have a latent 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 hypothesis that can explain why initial shocks can have a larger impact later in life.

Suppose 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, supposing 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. Besides, 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:

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

And the contemporaneous health condition follows:

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

Where $c_t = \ln(C_t)$, $h_t = ln(H_t)$, 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, then have:

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

Then have

$\delta = \ln(a) + \beta b_0 + \beta b_1 b_0 + \beta b_1^2 b_0$, $\delta_1 = \beta b_1^3$, $\delta_2 = (\beta b_1^2 b_2 + [(\alpha\gamma + \beta b_2)\gamma + \beta b_1 b_2])\gamma$, $\delta_3 = \alpha$, $\delta_4 = \alpha\gamma + \beta b_2$, $\delta_5 = \gamma\delta_4 + \beta b_2 b_1$. Hence, 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 ($|\delta_5| > |\delta_4| > |\delta_3|$). Here are three hypotheses related to this model:

Hypothesis I: The early health shock, i.e., air pollution, has 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 shock on human capital becomes more apparent as the child ages. This implies $|\delta_5| > |\delta_4|$.

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

To test the hypotheses, I modify (1) to include controls for potentially confounding factors. The basic econometric model is:

(2) $$\ln(S_{icl}) = \delta P_{t^b c} + \beta X_i + \theta Z_s + \gamma Y_c + \varepsilon_{icl}$$

where S_{icl} represents *S* in our model and it is the score of individual i, city *c* and subject *l*. The air pollution at birth, which represents the early health shocks as u_{t-3} in the model, is denoted by $P_{t^b c}$. $P_{t^b c}$ is air pollution of city *c* at birth time t^b.

In the regression, I add control variables including students' and household's characteristics, school features and city characteristics. X_i is the characteristics of the student and her household, including student's age, gender, age entering primary school, number of siblings, parents' education and income. Z_s is the characteristics of the school such as school quality, school type (e.g., public or private), and distance from home. Y_c is the city characteristics including GDP per capita, temperature and wind speed, and city fixed effect. To allow heterogeneous correlation, the standard errors are clustered at the city level.

To test *Hypothesis I*, I expect δ to be significantly negative, which means the air pollution at birth brings negative impact on student's academic performance. Measurement error in the air pollution measures could be correlated with the error term if, as an example, student academic performance is related to factors that would lead officials to understate pollution levels. As I mentioned above, although there is argument that our data might be free from manipulation, this study still want to pay attention to this issue.

I follow the method of Sanders (2012), who uses the share of manufacturing employment in counties of Texas as an instrumental variable of TSP for a period of 1981-1983. The intuition is the manufacturing sector experiences decreases in both employment and capacity utilization, and employment shifts to other sectors like retail and service (Orrenius, Saving and Caputo, 2005). The change of manufacturing sector is correlated with air pollution level. In United States, the industry's contribution to total national particulates was down to 37 percent by 1985 after the manufacturing sector employment shrank. (Environmental Protection Agency 1985; Chay and Greenstone 2003). A similar thing happens in China during 1989-2004. As Figure 3 shows, the share of manufacturing employment decreases sharply during this period of time. I use the city-level relative share of manufacturing employment (manufacturing employment divided by all employment) as an instrument for TSPs.

$$TSP_{year\ of\ birth} = f(relative\ share\ of\ manufacturing\ employment)$$

In Figure 4, I separate the cities into three groups according to their changing manufacturing employment share during 1989 to 2004. The third of the cities experiencing the largest decline in manufacturing employment share also experienced more air pollution reduction during 1989 to 2004. The bottom third of the cities experiencing the smallest decline in manufacturing employment share had relatively small improvements in air quality.

To test *Hypothesis II* and *Hypothesis III,* I run (2) on data from different age groups and add air pollution after birth into the regression. The coefficient β_1 is expected to be larger at older ages, and the coefficient of air pollution at birth is expected to be larger than the coefficient on air pollution after birth.

5. Empirical results

5.1 *OLS results*

In the following regressions, I control for the school grade, school quality, school type, parents' education and their income, city economic demographics and children's characteristics in all regressions. In all regressions, I cluster the error term by cities for CHIP and by provinces for CFPS.

Table 2 lists the empirical results of model (2) using CHIP 2009 with exam scores as the dependent variables. This dataset allows a match between the data of metropolitan air pollution at birth and the individual's test scores. Air pollution has a significant negative effect on a student's Literature (or Chinese) and Math test scores. As column 1 and column 5 show, a one standard deviation (120 $\mu g/m^3$) increase in total suspended particulates will lower the literature score by 2.16 percent, and it will lower the math score by 2.76 percent. Then, I add weather variables into the regressions in the column 2 and 6. Still, a one standard deviation increase in TSP lowers math score by 3.48 percent, and it lowers literature score by 2.16 percent after adding the weather factors. The increasing magnitudes of the coefficient indicates that the weather variables are correlated with pollution indicators such that excluding the confounding effects of weather understates the estimated pollution effects. These results support the ***Hypothesis I*** that air pollution at birth has an adverse impact on academic performance in later life.

In all regressions, girls significantly perform better than boys in studying literature. Birth weight has a negative and significant impact on literature study for girls. For all the children, their scores of math and literature decline with age. It is probably because the difficulty of the exam increases with their grades.

In Table 2, I also report related results when I combine air pollution data with the CFPS 2012. As it is mentioned before, I can only merge the air pollution data at the provincial level. However, the CFPS data include the parent's as well as the children's scores on a standard word test and a math test. Including the parents' test scores allows for better control of inherited ability from the parents which could be correlated with air pollution. Columns 3 and 4 in Table 2 report the impact of TSP at birth on children's math test score. Column 3 implies that a one standard deviation increase in TSP at birth lowers the math score by 2.28 percent without inclusion of parents' scores. When the parents' math scores are added into the regression, as column 4 shows, the TSP at birth has a positive non-significant impact on children's math performance. For the standard word test score, as column 7 and 8 show, a one standard deviation increase in total suspended particulates lowers the literature test score by 4.2 when parents' scores are not included, and the effect gets even larger, implying a 5.28 percent reduction when parents' scores are included. Ignoring the parents' test scores may cause a bias when I test the correlation between air pollution at birth and current test scores. These results support ***Hypothesis I*** that air pollution at birth has an adverse impact on students' academic performance. The severe air pollution at birth has a profound detrimental impact on cognitive ability in later life.

As before, girls have a better performance in the standard word test than boys. School quality has a significant positive impact on students' performance in both Math and Word tests. Father's word test score positively affects children's word test score. Finally, older children performance better than the younger ones. It is reasonable since the difficulty of the tests in CFPS are adjusted by recipient's age. With the ongoing brain development, the older cohorts are likely to perform better than the younger ones.

To test ***Hypothesis II***, I do the same analysis on different age groups. Specifically, the sample is divided into two subgroups: those who are in the high school and students who are in the elementary school. The average age is 12 years old for high school students in China. Table 3 provides the empirical results on both groups. The second and fourth column suggest that suspended particulates at birth has a larger and more significant impact on students' academic performance in early adulthood than later childhood. For those who are older than 12 years old, a one standard deviation increase of TSP will lower the literature and math scores by 3.72 and 7.56 percent, respectively. For the younger children, it has no significant adverse impact on their math and literature scores. The impact of air pollution at birth on academic performance is not significant for the children who are younger than 12 years old. These results support our ***Hypothesis II*** that the impact of early health shock on human capital becomes more apparent as the child ages.

To test ***Hypothesis III***, I add air pollution levels after children's birth into the analysis, and I estimate empirical specification (2) below, and I expect the magnitude of the coefficient of air pollution at birth is greater than the magnitude of the coefficients of other air pollution, i.e., $|\delta_1| > |\delta_n|$ for $n \geq t^b + 1$

$$(1) \qquad \ln(S_{icl}) = \delta_1 P_{t^b c} + \sum_{n=t^b+1} \delta_n P_{nc} + \beta X_i + \theta Z_s + \gamma Y_c + \varepsilon_{icl}$$

Table 4 shows that how air pollution at different periods in the student's life affects the student's academic performance. Columns 1 and 3 show that when I add the air pollution in the three years after birth into the regression, a one standard deviation increase of TSP at birth lowers literature scores by 1.92 percent, and it lowers math scores by 3.48 percent. When air pollution levels of the six years after birth are added (columns 2 and 4), a one standard deviation increase in TSP lowers the literature score by 2.04 percent, and it lowers math score by 3.96 percent. I find consistently that the effects of air pollution levels after birth, are smaller than the effects at birth, although most effects of pollution on academic performance later in life are also negative. Our findings are consistent with ***Hypothesis III*** that the largest adverse effects of air pollution come from pollution levels at birth.

Figure 5 and 6 show the heterogeneous impacts of air pollution on math scores and literature scores for different birth cohorts. These graphs depict the 95% percent confidence interval of the coefficients estimated in Table 2. The estimated coefficients are mostly negative, which indicates the detrimental impact of air pollution on cognitive ability development in long run.

Similar to the previous finding in Table 2, student's performance in math and literature declines with their ages. Besides, father's education and tutoring class now have positive impacts on students' scores in math test, and the boys have a better performance in math test than girls.

5.2 *2SLS results*

As it has been mentioned in Section 4, I use manufacturing employment share as an instrumental variable for air pollution, following the adoption of Sanders (2012) who found manufacturing industry contributes to the air pollution in Texas during 1980s. In Sanders (2012), he found the share of employment in manufacturing sector was closely correlated with TSP. As it has been mentioned above, Figure 4 plots the changes of manufacturing employment and air pollution. The cities with the most manufacturing employment share's decline also experienced a greater improvement of air quality. Also, as Panel B of Table 5 shows, manufacturing ratio of employment at birth year is positively correlated with the total suspended particulates at birth. One percent increase in manufacturing employment share is linked with 240 $\mu g/\mathrm{m}^3$ suspended particulates, which is equal to two standard deviation of TSP at birth. The three statistics (Crag-Donald F statistics, Kleibergen-Paap F statistics, and Sanderson-Wingdmeijer P-value[7]) all show that the instrument variable is a strong instrumental variable. Figure 7 depicts the measurement differential in air pollution between Chinese government and a credible source from U.S. embassy in China. U.S. embassy began to monitor air pollution since 2010s in three cities of our sample, Shanghai, Guangzhou and Chengdu[8]. Figure 7 shows the relation between the manufacturing employment share and measurement bias between the two institutions. There is a negative and non-significant correlation between the two factors, which makes the instrumental variable even more solid. The Panel A of Table 5 lists the 2SLS results. Air pollution at birth has a significant negative impact on young students' math exam scores, while the impact becomes insignificant for literature exam scores. The column 1 and 3 in Table 6 give the baseline 2SLS results. A one standard deviation increase of TSP will lower the math exam scores by 5.28 percent, and it lowers the literature exam scores by 0.12 percent while not significant. Compared with the results when TSP is regarded as exogenous variable, the impact becomes larger for the math exam scores, and it becomes smaller for literature exam performance.

In columns 2 and 4 in Table 6, I add weather indicators including temperature and wind speed into the regression. A one standard deviation increase of TSP will lower the math scores by 4.56 percent and there is no detrimental impact on the literature score. Compared with the results in columns 1 and 3, the adverse impact of air pollution at birth becomes smaller when weather factors are added into analysis. It suggests the weather is a confounding factor in our study. Meanwhile, the magnitude of the impact of air

[7] The three statistics are used to test the weakness of the instrumental variable. The null hypothesis is the instrumental variable is a weak instrumental variable.

[8] The air pollution data of U.S. embassy in Shanghai and Guangzhou are available since 2011, and the air pollution data in Chengdu are available since 2012. Additionally, I exclude the air pollution data of Shanghai in 2011 and Guangzhou in 2011 and 2012 since the air pollution was monitored with few months in those years.

pollution at birth on math score is greater than the results of ordinary least square estimation.

5.3 Robustness check

Previous research found that air pollution has different impacts in utero depending on fetal maturity (Currie and Schwandt, 2016). The impact is most significant for the first trimester. Since I don't have the precise birth date, the first trimester may be in the year before the birth year. I add the air pollution level before the birth year and after the birth year into our regression. As Table 6 shows, air pollution at birth still adversely affects the math scores and literature scores, while the impact on literature exam scores are not significant when including air pollution before birth. Though the coefficient of the following year's air pollution is positive and significant on math scores, the net effect of air pollution is still negative and significant. As columns 1 to 3 of Table 6 show, the magnitude of the coefficient of air pollution at birth increases when air pollution around birth year is added into regression. This result may just reflect the fact that the air pollution levels are correlated with each other for contiguous years. Anyway, a one standard deviation increase in TSP lowers the math score by 3.24 percent when the air pollution of the year before birth is added, and it lowers the math score by 3.6 percent when both the pre-birth and post-birth air pollution levels are added into regression. Similarly, a one standard deviation increase in TSP lowers the literature score by 2.04 percent when the pre-birth air pollution is added. And it lowers the literature score by 1.32 percent when both the pre-birth and post-birth air pollution levels are added. The impact is greater for math performance compared with our baseline model. Since the overall impact of the air pollution around birth is still negative, I can see the air pollution in utero and very early childhood has a detrimental impact on later cognitive skill development.

The air pollution affects youth health. It not only affects their cognitive development, but also affects youth maturity. Case and Paxson (2008) regard height as a measure of health and find it correlated with future earnings and cognitive skills. In this sense, exposure to air pollution early in life may have a particularly large adverse effect on youth development other than the test scores in schools. Table 7 shows that air pollution negatively affects youth height and weight[9] in China. As Table 7 shows, TSP at birth negatively affects youth current height and weight, while the impact is not significant for current weight. The column 1 suggests that a standard deviation increase of TSP at birth lowers youth height-for-age by 0.84 percent for the kids aged between 7 and 19. Although the impact is not significant for youth weight, the estimated relationship between air pollution and weight is still negative for the children between 7 to 19 years old. The air pollution at birth also has an adverse impact on youth maturity.

Since air pollution at birth has an adverse impact on children's academic performance, presumably it will lower their potential income in adulthood. In Table 8, I test the correlation between test scores and annual income using CFPS 2012. The word test score and math test score are both positively correlated with annual income. Particularly, one percentage increase in math test score will lead to a 2.68 percentage increase in annual income. By the previous finding from the column 3 and 7 of Table 2, a one standard deviation increase in TSP at least lowers math test score and word test score by 2.28 and 4.2 percent, respectively. Therefore, a one standard deviation increase in total suspended particulate at birth will lower the annual income by 6.11 percent. The air pollution at birth reduces young generation's potential income. The improving air quality from 336 $\mu g/m^3$ to 229 $\mu g/m^3$ in 1990s (e.g., 1990~2000) raises the annual income of youth by 5.45 percent.

6. Conclusion

In this study, I find a significant negative impact of air pollution at birth on youth's cognitive development in China. OLS results shows that a standard deviation increase of total suspended particulate lowers the literature score by 2.16 to 2.52 percent, and it lowers the math score by 2.76 to 3.48 percent. The 2SLS result shows that a standard deviation increase of TSP at birth lowers literature score by 0.12 percent and lowers the math score by 5.28 percent. This study also uses standard word test and math test as dependent variable. The empirical results show that a standard deviation increase

[9] The height and weight are normed by national standard height and weight by different ages and genders in cities.

of TSP lowers literature test outcome by 4.2 to 5.28 percent, and it lower math score by 2.28 percent.

The air pollution has a profound impact on the development of youth. Zhang et al. (2008) studied the short-run impact of air pollution on cognitive performance for the whole population by using the air pollution index (API) published since 2004. They found a one standard deviation increase in air pollution index within 7 days lowers the test score by 1.6 percent, and it lowers the math test score by 0.6 percent. A one standard deviation increase in the cumulative air pollution, which refers to the average API within 3 years, will lowers the word test score and math test score by 6.3 and 1.9 percent, respectively. This study differs from theirs in three aspects. First, the air pollution not only has a contemporary impact on brain functioning, but also affects the cognitive skills formation in a long run. Moreover, the early life shocks may have a greater impact than the later ones since the early negative impact accumulates through time. The negative impact of air pollution becomes more apparent when children ages. In this study, I focus on a persisting impact of air pollution on cognitive development. This sutdy found a stronger impact of air pollution at birth on the cognitive skill in math in the long run. A one deviation increase in total suspended particulate lowers the math test score up to 3.48 percent. At the same time, this study found the air pollution at birth also affects youth maturity. Besides, this study provides the evidence that early health shock at birth (i.e., air pollution at birth) has a stronger impact on ongoing cognitive skill development, compared with the later shocks in life. Depressed cognitive development will lower their human capital accumulation and productivity. Currie and Thomas (2001) find a standard deviation increase in test scores at age 16 is associated with 11-14 percent higher wages and a 3-7 percent higher employment probability at age 33. Graff Zivin and Neidell (2012) find a 10 ppb change in ozone exposure results in a 5.5 percent change in agricultural worker productivity in United States. The air pollution at birth will lead to a huge human capital loss with severe air quality and huge population in China. I test the correlation between annual income and test scores using CFPS 2012. One percentage increase of math test score significantly leads to 2.68 percentage increase of annual income. The coefficient of word test score is positive while it is not significant. Overall, a one deviation increase of total suspended particulate at birth will lower the annual income by 6.11 percent. These results remind the policy makers the importance of reducing air pollution in China. The severe air pollution not only lead to a current economic cost, but also hinder the human capital accumulation in this country.

Although this study has explained some mechanisms by which air pollution at birth may affect later human capital outcome, the picture is not clear enough. Future work needs more information about children's health conditions through their childhood. For example, Currie et al. (2010) test how the health conditions in different ages of the same kid affect young adult outcomes.

Besides, it is interesting to test how the air pollution will affect youth's behavior and non-cognitive skill development. Air pollution at birth has been proven a great impact on behaviors in later life (Reyes, 2015). There is no literature about how the air pollution will affect youth psychological health in China.

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Tables and Graphs

Table 1 Data Description

Variable	Observation	Mean	Standard Deviation	Min	Max
Chinese Household Income Project (CHIP) 2009					
Math	933	0.85	0.12	0	1
Chinese	933	0.84	0.11	0	1
Gender (F=1)	933	0.47	0.50	0	1
Age	933	12.76	3.84	3	19
Birth Weight (/gram)	933	3,374.39	617.29	350	8,300
Age entering school	933	6.50	0.56	5	8
Father's Income (Log)	890	6.68	2.94	0	10.31
Mother's Income	922	5.76	3.19	0	9.80
Number of children	922	0.17	0.39	0	3
Father's education (/y)	886	12.35	3.26	3	31
Mother's education	921	11.65	3.14	2	35
Public School	933	0.92	0.26	0	1
Private School	933	0.07	0.26	0	1
School Quality					
Best	930	0.14	0.35	0	1
Better than the average	930	0.52	0.50	0	1
About the average	930	0.33	0.47	0	1
Lower than the average	930	0.01	0.09	0	1
Distance from home and School (km)	930	19.45	124.84	0	2,000
Boarding School	931	1.84	0.37	1	2
Expenditure on tutoring within school	932	237.38	651.67	0	12,000
Expenditure on tutoring out of school	932	1,259.09	2,406.47	0	36,100
TSP at birth (μg /m^3)	924	0.26	0.12	0.09	0.81
GDP per capita at birth	933	11,756.86	9,223.85	1,111	60,801
GDP per capita at test date	933	57,065.32	18,440.41	19,924	83,431
Temperature of test date	933	17.57	2.45	14.40	22.80
Birth year lowest temperature	686	56.73	4.68	48.00	68.40
Birth year highest temperature (F)	686	70.76	3.83	67	81.10
Birth year average temperature (F)	686	63.74	4.13	57	74.40
Heating hours in birth year	676	2,741.74	941.83	436	4,192

Wind speed in birth year	676	8.60	1.66	4.41	15.38

Table 2 Air Pollutants at birth and exam scores (Literature and Math)

VARIABLES	Log(math exam score)	Log(math exam score)	Log(Literature exam score)	Log(Literature exam score)
	CHIP2009		CHIP2009	
TSP (milligram/m^3)	-0.23**	-0.29*	-0.21**	-0.18*
	(-2.39)	(-2.15)	(-2.39)	(-2.03)
Gender (M=0, F=1)	-0.02**	-0.02	0.00	0.01
	(-2.49)	(-1.68)	(0.34)	(0.38)
Age	-0.02***	-0.02*	-0.01*	-0.01
	(-3.42)	(-2.35)	(-1.85)	(-1.40)
Birth Weight	-0.00	-0.00	-0.00*	-0.00**
	(-1.72)	(-1.65)	(-2.14)	(-2.95)
Log(father's income)	-0.00	-0.00	0.00	0.00
	(-1.37)	(-0.63)	(0.26)	(0.28)
Log(mother's income)	0.00	0.00	0.00	0.00
	(0.08)	(0.07)	(1.34)	(0.82)
Number of Siblings	-0.03	-0.03	-0.03	-0.03
	(-1.62)	(-1.01)	(-1.40)	(-0.93)
Father's Education (/Yrs)	0.00***	0.00**	0.00	-0.00
	(3.69)	(3.14)	(0.35)	(-0.59)
Mother's Education	0.00	0.00	0.00	0.00*
	(0.66)	(1.04)	(0.92)	(2.25)
Boarding School (Y=1)	0.00	-0.00	0.02	0.01
	(0.18)	(-0.07)	(1.30)	(1.22)
Father's Test Scores	N.A.	N.A.	N.A.	N.A.
Mother's Test Scores	N.A.	N.A.	N.A.	N.A.
Tutoring classes[1]	-0.00	-0.00	0.00	0.00
	(-0.80)	(-0.52)	(0.53)	(0.58)
Tutoring classes[2]	0.00	0.00	0.00	0.00
	(1.03)	(0.69)	(0.54)	(0.45)
Include School Grade of Child	Y	Y	Y	Y
Include School Quality	Y	Y	Y	Y
Include School Type	Y	Y	Y	Y
Include Parent's Education	Y	Y	Y	Y
Include the time duration with parents	Y	Y	Y	Y
Include location fixed Effect	Y	Y	Y	Y
Include Weather Variables	N	Y	N	Y
Observations	849	628	849	628
R-squared	0.39	0.40	0.40	0.38

[1,2]Tutoring classes include the classes provided within schools and the ones provided by private institutions. Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1.

Table 3 Heterogeneous Test: Air pollution at birth and exam scores (Literature and Math)

VARIABLES	Literature		Math	
	Age under 12	Age above 12	Age under 12	Age above 12
TSP at birth	-0.16	-0.31**	0.01	-0.63***
	(-1.11)	(-2.82)	(0.15)	(-4.32)
Age	-0.00	-0.01	-0.02**	-0.03
	(-0.19)	(-0.58)	(-3.05)	(-1.55)
Gender (F=1)	0.00	0.01	-0.00	-0.03*
	(0.28)	(0.89)	(-0.54)	(-1.84)
Birth Weight	-0.00	-0.00	-0.00	-0.00
	(-0.35)	(-1.40)	(-0.17)	(-1.17)
Father’s Income	-0.00	0.00	-0.00	-0.00*
	(-0.96)	(0.99)	(-0.65)	(-2.14)
Mother’s Income	0.00*	-0.00	0.00**	-0.00*
	(1.92)	(-1.52)	(2.26)	(-1.96)
Number of Siblings	-0.02	-0.04	-0.01	-0.06*
	(-0.73)	(-1.16)	(-0.64)	(-1.95)
Father’s Education (/Yrs)	0.00	0.00	0.01**	0.00**
	(0.47)	(0.04)	(2.53)	(2.38)
Mother’s Education (/Yrs)	0.00	0.00	-0.00	0.01*
	(0.63)	(0.81)	(-1.39)	(1.99)
Boarding School (Y=1)	-0.04*	0.00	-0.03***	-0.02
	(-1.86)	(0.32)	(-3.67)	(-0.97)
Tutoring Class out of school	0.00	0.00	-0.00	0.00**
	(0.19)	(1.35)	(-0.05)	(2.48)
Observations	396	413	396	413
R-squared	0.20	0.31	0.28	0.31

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1. This regression is based on CHIP 2009

Table 4 TSP impact on Literature and Math exam scores

VARIABLES	Literature exam score		Math exam score	
TSP_t	-0.16*	-0.17*	-0.29***	-0.33***
	(-1.97)	(-1.79)	(-3.62)	(-3.18)
TSP_{t+1}	-0.11	-0.11	0.04	-0.04
	(-1.05)	(-0.72)	(0.43)	(-0.27)
TSP_{t+2}	0.01	-0.07	-0.00	-0.07
	(0.04)	(-0.40)	(-0.01)	(-0.46)
TSP_{t+3}	0.03	-0.14	0.09	-0.01
	(0.22)	(-0.66)	(0.84)	(-0.07)
TSP_{t+4}		-0.02		0.05
		(-0.10)		(0.24)
TSP_{t+5}		0.21		0.07
		(1.30)		(0.39)
TSP_{t+6}		0.04		-0.12
		(0.39)		(-0.95)
Gender (F=1)	0.00	0.01	-0.02***	-0.02***
	(0.20)	(0.79)	(-3.51)	(-3.35)
Age	-0.01**	-0.01**	-0.02***	-0.02**
	(-2.65)	(-2.83)	(-4.97)	(-2.69)
Birth Weight	-0.00*	-0.00	-0.00	-0.00*
	(-2.06)	(-1.70)	(-1.76)	(-1.83)
Father’s Income	-0.00	-0.00	-0.00*	-0.00*
	(-0.40)	(-0.07)	(-2.03)	(-2.18)
Mother’s Income	0.00	0.00	0.00	-0.00
	(1.60)	(0.60)	(0.75)	(-0.35)
Number of Siblings	-0.02	-0.01	-0.02	-0.02
	(-1.13)	(-0.57)	(-1.25)	(-1.08)
Father’s Education	-0.00	-0.00	0.00**	0.00**
	(-0.22)	(-1.29)	(2.98)	(2.50)
Mother’s Education	0.00	0.00	0.00	0.00
	(0.60)	(0.75)	(0.83)	(1.06)
Tutoring Class out of School	0.00	0.00	0.00*	0.00**
	(1.06)	(1.61)	(1.96)	(2.51)
Observations	811	638	811	638
R-squared	0.47	0.51	0.52	0.49

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1. This regression is based on CHIP 2009

Table 5 IV estimates of the impact of prenatal pollution exposure of TSP on math and literature

	Log(Math Scores)		Log(Chinese Scores)	
	(1)	(2)	(3)	(4)
	Baseline IV results	Adding Weathers	Baseline IV results	Adding Weathers
Panel A: Second Stage Results				
TSP at birth	-0.44**	-0.38*	-0.01	0.34
	(-2.18)	(-1.81)	(-0.05)	(1.27)
Gender (F=1)	-0.01**	-0.01**	0.01	0.02
	(-2.44)	(-2.29)	(1.03)	(1.05)
Age	-0.01***	-0.00	-0.01	-0.00
	(-3.48)	(-0.86)	(-1.41)	(-0.30)
Income of Father	-0.00**	-0.00***	0.00	-0.00
	(-2.07)	(-3.30)	(0.02)	(-0.14)
Income of Mother	-0.00	-0.00*	0.00	0.00
	(-0.57)	(-1.78)	(0.87)	(0.58)
Father Education	0.00***	0.00*	-0.00	-0.00**
	(2.61)	(1.83)	(-0.53)	(-2.48)
Mother Education	0.00	0.00*	0.00	0.00***
	(0.65)	(1.67)	(1.14)	(2.63)
Panel B: First-stage results and test statistics				
Manufacturing Ratio	0.24***	0.18***	0.24***	0.18***
	(4.81)	(3.38)	(4.81)	(3.38)
CD F-statistics	40.31	33.42	40.31	33.42
KP F-statistics	23.15	11.44	23.15	11.44
SW p-value	0.0007	0.0196	0.0007	0.0196
Observations	699	483	699	483
R-squared	0.40	0.41	0.40	0.41

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1. This regression is based on CHIP 2009

Table 6 Heterogeneous Test: Air pollution around birth time and exam scores (Literature and Math)

VARIABLES	Log(Math Scores)			Log(Literature Scores)		
TSP_t	-0.27*	-0.27***	-0.30**	-0.17	-0.14*	-0.11
	(-1.80)	(-3.10)	(-2.25)	(-1.27)	(-2.05)	(-0.86)
TSP_{t-1}	0.06		0.05	-0.03		-0.03
	(0.67)		(0.52)	(-0.26)		(-0.32)
TSP_{t+1}		0.08	0.08		-0.08	-0.08
		(0.88)	(0.85)		(-0.90)	(-0.95)
Gender (F=1)	-0.02**	-0.02**	-0.02**	0.00	0.00	0.00
	(-2.58)	(-2.49)	(-2.50)	(0.32)	(0.35)	(0.32)
Age	-0.02***	-0.02***	-0.02***	-0.01*	-0.01	-0.01
	(-4.37)	(-3.79)	(-4.36)	(-1.99)	(-1.70)	(-1.74)
Birth Weight	-0.00	-0.00	-0.00	-0.00*	-0.00*	-0.00*
	(-1.67)	(-1.75)	(-1.72)	(-1.89)	(-2.01)	(-1.94)
Father's income	-0.00	-0.00	-0.00	0.00	0.00	0.00
	(-1.27)	(-1.37)	(-1.32)	(0.33)	(0.24)	(0.30)
Mother's income	-0.00	-0.00	-0.00	0.00	0.00	0.00
	(-0.13)	(-0.15)	(-0.20)	(1.11)	(1.17)	(1.08)
Number of siblings	-0.03	-0.03	-0.03	-0.03	-0.03	-0.03
	(-1.50)	(-1.50)	(-1.48)	(-1.40)	(-1.44)	(-1.43)
Father's Education	0.00***	0.00***	0.00***	0.00	0.00	0.00
	(4.06)	(4.06)	(4.05)	(0.37)	(0.43)	(0.38)
Mother's Education	0.00	0.00	0.00	0.00	0.00	0.00
	(0.79)	(0.86)	(0.85)	(1.12)	(1.14)	(1.21)
Observations	848	850	847	848	850	847
R-squared	0.38	0.38	0.38	0.39	0.39	0.39

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1. This regression is based on CHIP 2009.

Table 7 TSP at birth and youth's weight and height

VARIABLES	Height Relative to National Average by ages and genders	Weight Relative to National Average by ages and genders
TSP at birth	-0.07**	-0.04
	(-2.51)	(-0.22)
Gender (M=0, F=1)	-0.00	0.01
	(-0.55)	(0.90)
Age	-0.01***	-0.03***
	(-4.64)	(-6.27)
Birth Weight	0.00	0.00**
	(1.63)	(2.23)
Father's Income	0.00	0.00
	(0.66)	(0.26)
Mother's Income	-0.00	-0.00**
	(-1.66)	(-2.37)
Number of Siblings	0.01	-0.01
	(1.39)	(-0.73)
Father's Education	0.00**	0.00
	(2.36)	(0.76)
Mother's Education	0.00	0.00
	(0.98)	(1.04)
Observations	885	885
R-squared	0.13	0.13

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1. This regression is based on CHIP2009.

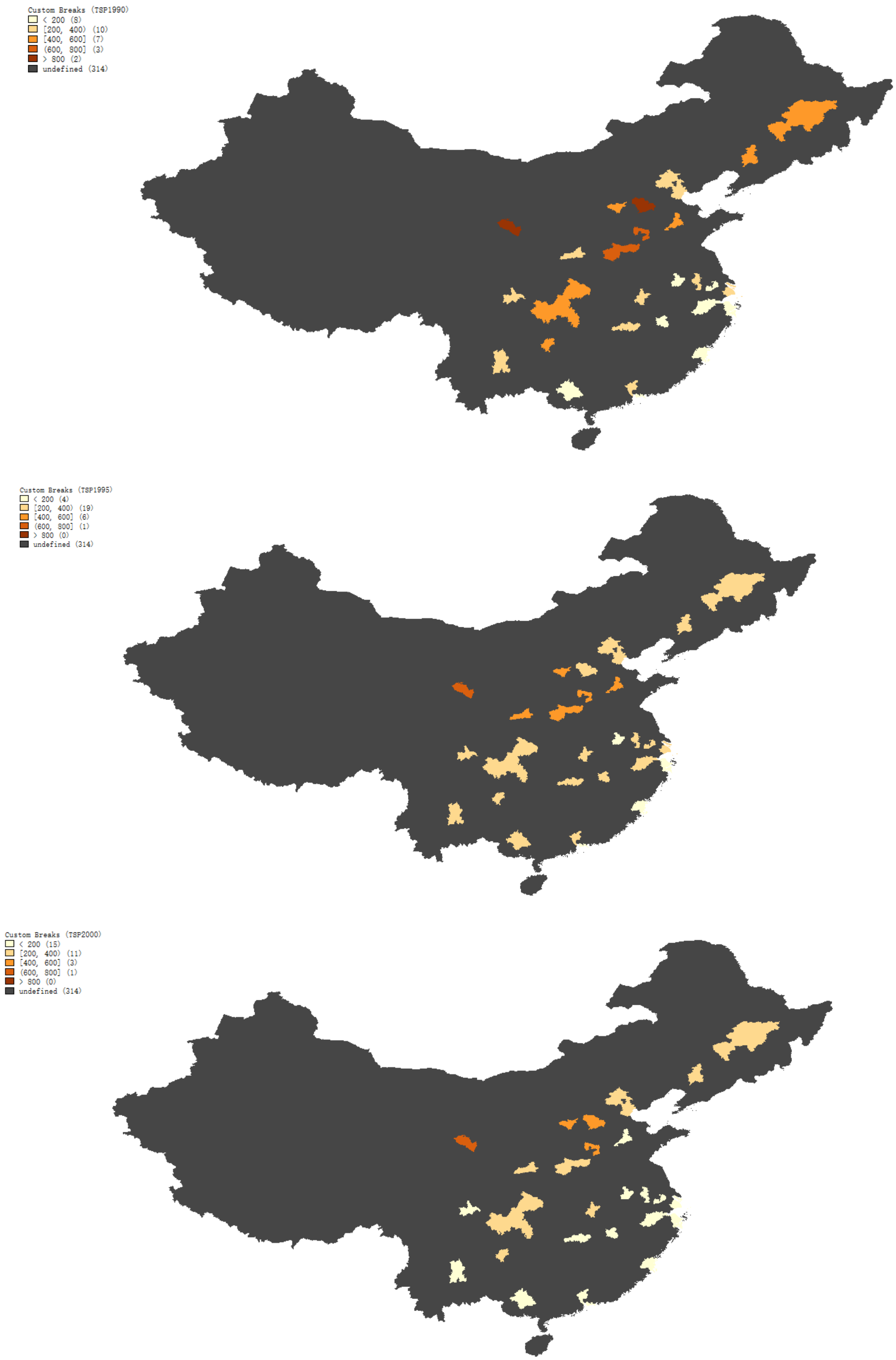

Figure 1 TSP of Chinese cities in 1990, 1995 and 2000
Source: DECRG

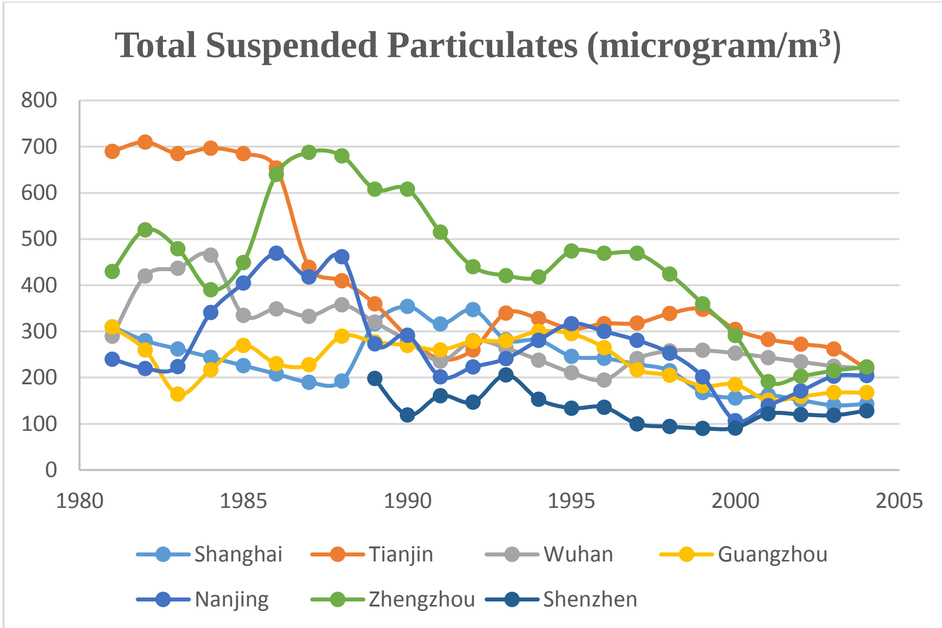

Figure 2 Annual daily average TSP of subsample of cities Data Source: World Bank and Chinese Environment Yearbooks

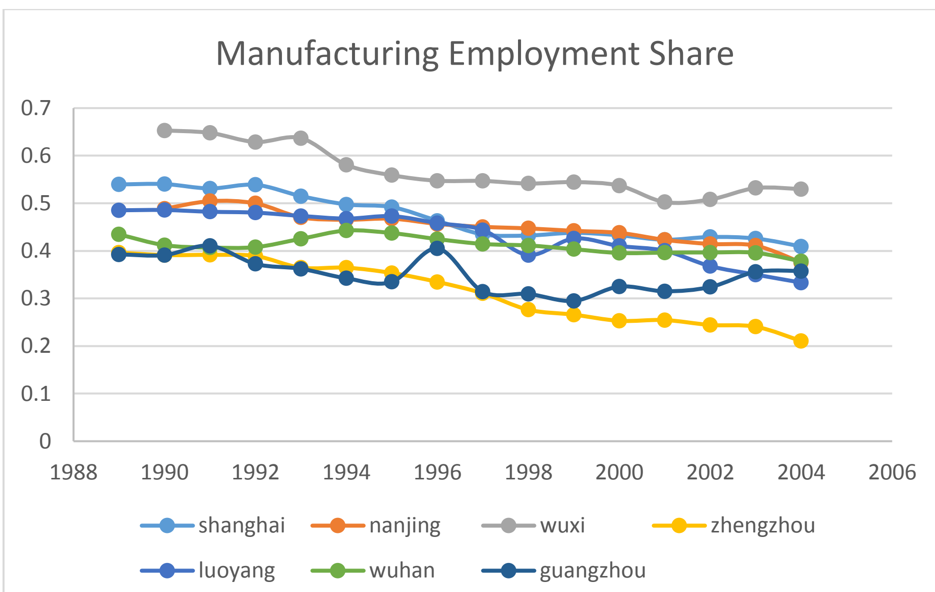

Figure 3 Manufacturing employment share between 1989 to 2004
Source: Chinese City Yearbooks

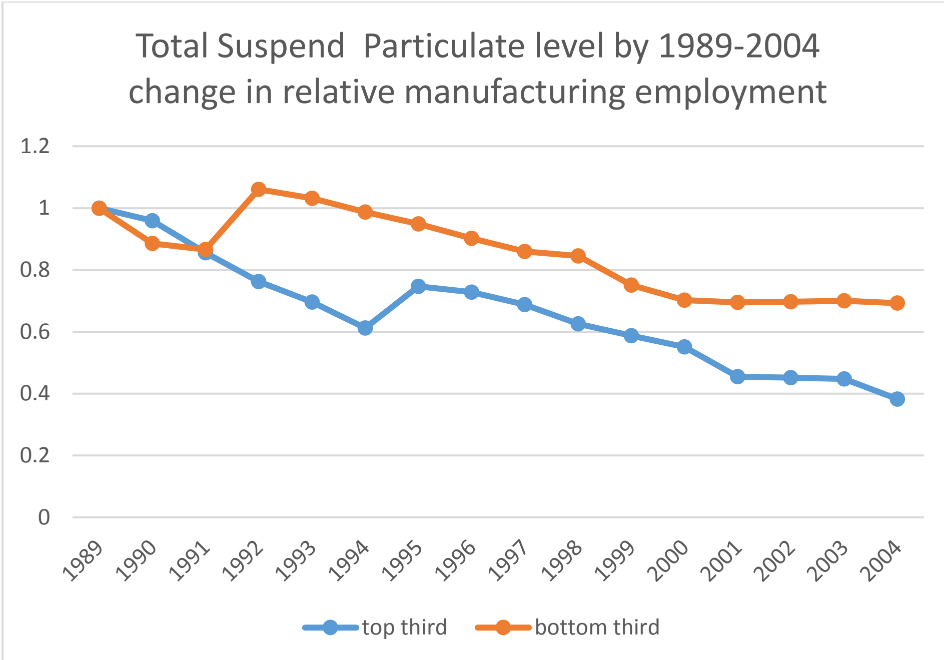

Figure 4 TSP level by 1989-2004 change in relative manufacturing employment

Note: Data are mean total suspend particulate level for a groups of cities studied in the study. Values are the tsp level relative to 1989 level. The cities are grouped into three groups by the change of manufacturing employment share decline during 19902004. Source: Yearbooks of each cities during 1989-2004.

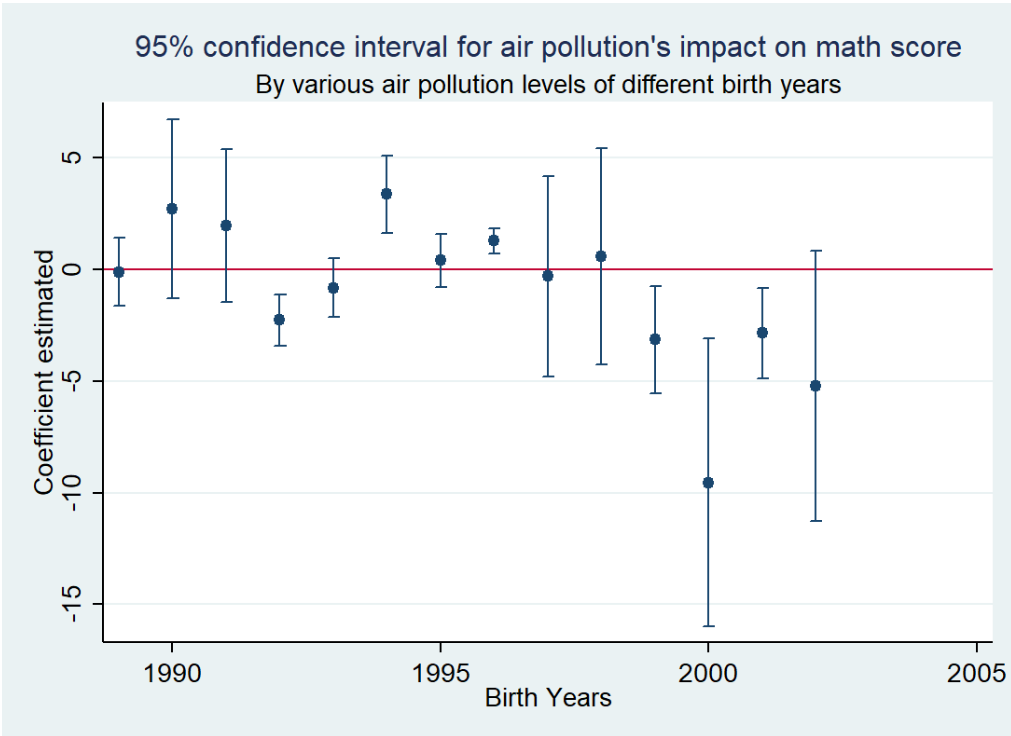

Figure 5 Impacts of air pollution at birth on math scores by different years

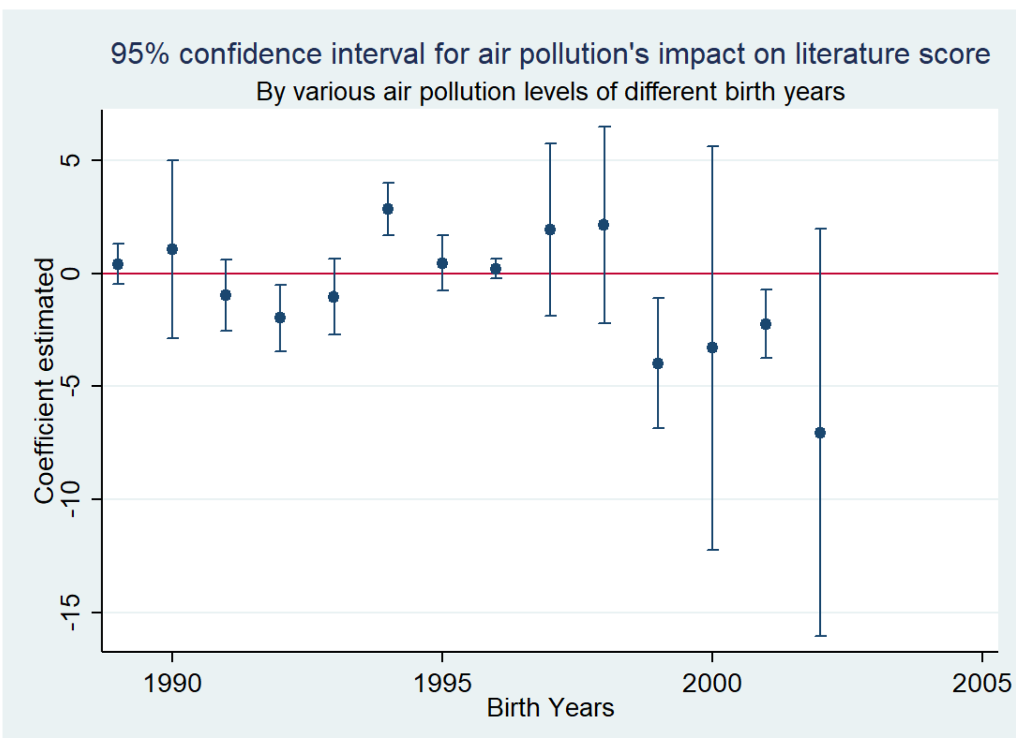

Figure 6 Impacts of air pollution at birth on literature scores by different years