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**Xin Zhang**
*Beijing Normal University*

**Yixuan Wang**
*Ohio State University*

**Xingyi Hu**
*Ohio State University*

**Xi Chen**
*Yale University and IZA*

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**IZA – Institute of Labor Economics**

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

# ABSTRACT

## Fetal Pollution Exposure, Cognitive Ability, and Gender-Specific Parental Investment

This paper examines the impact of fetal exposure to air pollution on low-stakes test performance across a broad age range, with a focus on gender-specific parental responses to this negative shock. Using data from a nationally representative survey in China, we find that fetal PM2.5 exposure significantly reduce cognitive ability in women, particularly those with brothers. Gender-biased human capital investment by families tends to amplify the harmful effects for girls, while diminishing these effects for boys. Specifically, when exposed to the same level of fetal PM2.5, females receive less homework assistance from their families and attain lower levels of education.

**JEL Classification:** Q53, I24, D13, J16

**Keywords:** air pollution, cognitive ability, fetal exposure, gender bias, parental investment

**Corresponding author:**
Xi Chen
Department of Health Policy and Management
Department of Economics
Yale University
New Haven
CT 06520
USA
E-mail: xi.chen@yale.edu

# 1 Introduction

Numerous studies have estimated the effects of early-life exposure to air pollution on children's abilities, subsequent development, and adult outcomes.[1] Most of these studies estimate the overall effect of early-life exposure to air pollution on various outcomes. However, early-life shocks influence later human capital not only through biological channels, but also parental involvement. Parents may reinforce, compensate for, or be neutral to their children's early revealed abilities. An improved understanding of this latter channel may promote interventions and policies that enhance social equity.

A growing body of research has studied the effect of child endowment on parental investment.[2] However, estimating the average effect may obscure significant heterogeneity across genders, particularly in countries like China where gender preference is prevalent. In such settings, girls and boys tend to receive a disproportionate share of resources, especially for credit-constrained families (Lei et al., 2017; Lin et al., 2021). Our paper explores gender-specific parental investment in response to children's fetal pollution exposure and its long-term impact on human capital formation, in a context where gender preference prevails. The study contributes to policy formulation by highlighting the importance of gender equity starting from early life and sheds light on policies aimed at narrowing gender gaps.

In this study, we examine the causal impact of fetal PM2.5 exposure on standardized verbal and math test scores across a wide age range of individuals in a nationally representative longitudinal survey in China. To address potential endogeneity in air pollution, we instrument PM2.5 concentrations using local wind direction and pollution of nearby upwind cities, a widely used instrumental variable (IV) strategy in recent studies (Zheng et al., 2019; Chen et al., 2021; Wang et al., 2022). We identify two channels through which fetal exposure

[1]See Currie et al. (2014) for a syntheses of this literature. Most studies mainly focus on the impact of early-life exposure to air pollution on short-term outcomes, such as infant mortality (e.g., Chay and Greenstone, 2003; Currie and Neidell, 2005; Greenstone and Hanna, 2014; Tanaka, 2015; Knittel et al., 2016) and child health (e.g., Neidell, 2004; Lleras-Muney, 2010; Schlenker and Walker, 2016). However, relatively few studies make a direct connection between early-life exposure to air pollution and longer-term outcomes.

[2]See Almond and Mazumder (2013) for a comprehensive literature review on fetal origins and parental responses.

to air pollution affects child human capital formation. The first is a biological channel, operating directly through the production function for human capital. The second is a family investment effect, stemming from parental responses to the shock. In the son-favored context of China, parents often allocate more resources to their sons to remediate the damage caused by prenatal PM2.5 exposure. Consequently, parental actions tend to amplify the gender gap in the effects of early-life shocks on human capital outcomes.

Our IV estimates suggest that a one standard deviation (SD) increase in fetal PM2.5 exposure leads to a decline in verbal and math test scores by 0.122 SD and 0.170 SD, respectively. Our findings reveal significant gender differences, with females being more vulnerable to the detrimental effects of PM2.5 exposure on both verbal and math abilities, especially when they have (male) siblings. To explain this gendered pattern, we test several potentially competing channels, including mortality selection, selection into motherhood, fertility decisions, and gender-specific investments by families. We find that gender-biased human capital investment by families limits girls' access to education and household resources, resulting in worse cognitive skills compared to boys when exposed to negative shocks *in utero*. Our estimates indicate that, when exposed to the same level of fetal PM2.5, females receive less assistance with homework from family members and achieve lower levels of education compared to their male counterparts.

This paper aims to contribute to the literature on several fronts. First, our study adds to the burgeoning literature on how parental investments respond to health endowments at birth and whether the postnatal investments are compensatory or reinforcing (e.g., Li et al., 2010; Yi et al., 2015; Adhvaryu and Nyshadham, 2016; Restrepo, 2016; Fan and Porter, 2020; Sanz-de Galdeano and Terskaya, 2022). We identify sex-selective postnatal investments as a new pathway through which fetal exposure to PM2.5 may lead to gender disparities in cognitive abilities. The literature on the gender-biased intra-household resource allocation primarily examines the short-term impact of negative shocks (Behrman, 1988; Behrman and Deolalikar, 1990; Cameron and Worswick, 2001; Thomas et al., 2004), while we focus on the long-term impacts. Moreover, larger female schooling responses to early-life health shocks have been documented in previous studies (Field et al., 2009; Maccini and Yang, 2009; Hoynes et al., 2016), but the reasons for these gender differences are relatively less well explored, especially from socioeconomic perspectives. Our study provides one of the first pieces of empirical evidence that gender preference can lead to gender disparities in postnatal parental investments, potentially affecting long-term outcomes.[3]

Second, studies examining the impact of air pollution on cognitive performance have mainly concentrated on its transient effects during the tests (e.g., Ebenstein et al., 2016; Zhang et al., 2018b; Cook et al., 2023; Krebs and Luechinger, 2024) or the effects of cumulative exposure over the years (Ham et al., 2014; Zhang et al., 2018b). However, evidence regarding the impact of prenatal exposure to air pollution on long-term cognitive performance is relatively limited. Our paper speaks directly to several economic studies on the relationship between *in utero* air pollution exposure and later-life cognitive abilities.[4] One paper closely related to ours is Molina (2021), which estimates the long-term effect of *in utero* pollution exposure by gender based on data from Mexico. She finds that exposure to pollution in the second trimester leads to significantly lower adult cognitive ability for both genders, but lower high school completion and income for women only. She further reveals that the gender differences in investment responses arise from gender-specific labor market

[3]One paper closely related to ours is Wu et al. (2023), which finds that parents are more likely to compensate for girls under positive rainfall shocks in early life. In contrast, our paper demonstrates that parents are more likely to invest in boys when faced with negative pollution shocks. Providing compensation to individuals with fewer advantages (females) during positive shocks acts as a safety net against economic volatility, while protecting individuals with advantages (males) during negative shocks helps mitigate risks and uncertainties associated with adverse events. Both of these actions can be viewed as risk-averse strategies, as they aim to minimize potential negative impacts on individuals, promote stability, and mitigate the risks associated with income inequality.

[4]For example, Sanders (2012) examines the impact of prenatal suspended particulate pollution on standardized test scores in high schools, using changes in relative manufacturing employment as an IV. However, their IV could affect test scores through channels other than air pollution, such as local educational funding and household income. Bharadwaj et al. (2017) analyze the impact of fetal exposure to CO and PM2.5 at the trimester level on math and language skills in the fourth grade in Chile. They employ a fixed-effect model and sibling comparisons to address concerns about residential sorting and time-invariant family characteristics. However, they neglect the effect of parents' differentiated investments in their offspring based on gender and birth order. Rosales-Rueda and Triyana (2019) estimate the effects of early-life exposure to air pollution using Indonesia's forest fires as a natural experiment. They find that children exposed to the fires *in utero* have worse health outcomes but do not suffer significant negative effects on cognitive function.

expectations. Our paper also documents gender differences in responses to early-life shocks, but provides an alternative explanation.

Third, we estimate fetal exposure to air pollution on the low-stakes cognitive performance of adults and adolescents.[5] Existing studies mainly focus on the high-stakes exams taken by school-aged children (Sanders, 2012; Bharadwaj et al., 2017). However, the low-stakes cognitive tests in our study are close to our day-to-day cognitive activities. Our findings suggest that the quality of routine decision-making processes is compromised by fetal PM2.5 exposure.

Finally, few studies have investigated the impact of fetal exposure to air pollution on cognitive performance and parental responses in developing countries, primarily due to data limitations. However, examining these impacts in developing countries is crucial, as pollution levels are typically higher and overall health status is often poorer compared to more developed nations.[6] Moreover, parental responses to early shocks in children may be more important in developing countries with weaker health infrastructure, less developed credit markets, and inadequate social protection systems. Therefore, the role of the family must be taken into account when designing public policies to remedy inequality at birth or during early childhood.

The rest of the paper is organized as follows: Section 2 presents a basic conceptual framework to help guide the empirical analysis; Section 3 introduces the data we use to perform the analysis; Section 4 presents our econometric strategy; Section 5 displays the main results, including the baseline results, robustness checks, and heterogeneous effects; Section 6 explores and tests some potential mechanisms, and Section 8 draws conclusions.

[5] As the data on air pollution is only available after 1980 and only interviewees above age 10 are required to take the cognition tests, the final datasets include respondents born between 1980 and 2000, who were aged between 10 and 30 at the time of the survey.

[6] For example, 98.6% of the population in China was exposed to PM2.5 at unsafe levels during 2013–2014 according to the World Health Organization (WHO) guideline (Long et al., 2018).

# 2 Conceptual Framework

How might fetal exposure to ambient air pollution affect child and adult outcomes? This paper focuses on the impact of fetal exposure to PM2.5, i.e., particulate matter with a diameter smaller than 2.5 μm. PM2.5 is known to have more detrimental effects on health compared to larger particulates, which are typically trapped in the upper airways and can be cleared by mucociliary mechanisms. However, due to its minuscule size, PM2.5 can penetrate the lungs at the alveolar level and release toxic substances into the bloodstream, leading to respiratory and cardiovascular diseases. These detrimental effects are particularly pronounced *in utero*. The decreased oxygen supply or organ damage experienced by pregnant women results in reduced oxygen transfer to the fetus, which hinders fetal brain development. Moreover, the particulates can directly pass through the bloodstream to reach the fetus, posing a risk to the development of the fetal respiratory and cardiovascular systems.

All of these *in utero* physiological impacts can translate into damages to cognitive function as a child develops and transitions into adulthood. Consequently, fetal exposure to air pollution can affect long-term human capital development due to direct health impairments. Additionally, parental investments play a crucial role in shaping human capital formation, and these investments are influenced by the health endowments at birth. Hence, fetal exposure to air pollution may also indirectly affect long-term human capital formation through family investments.

To differentiate between these two channels, we propose a simple framework based on the conceptual model presented in Currie et al. (2014). Our framework categorizes life into three distinct stages: fetus, childhood, and adulthood. The fetus stage begins *in utero* and ends at birth. Childhood starts at birth and encompasses the entire duration of schooling. Adulthood can be perceived as the post-schooling period, during which individuals typically enter the workforce.

Assume that fetus ($F$) human capital $H_F$ is dependent on fetal exposure $P_F$ and family characteristics $X$, such as genetics, where $\partial f_F/\partial P_F < 0$:

$$H_F = f_F(P_F, X) \tag{1}$$

Childhood ($C$) human capital $H_C$ is a function of childhood pollution exposure $P_C$ and human capital accumulated *in utero* $H_F$, where $\partial f_C/\partial P_C < 0$, and $\partial f_C/\partial H_F > 0$. Importantly, families can make investments $I_C$ in their children, with $\partial f_C/\partial I_C > 0$, indicating that an increase in investments made by the family results in higher levels of childhood human capital. It's worth noting that the investments made by families may rely on the initial human capital endowment at birth.

$$H_C = f_C(P_C, H_F, I_C(H_F)) \tag{2}$$

Finally, adult ($A$) outcomes $H_A$ depend on adult pollution exposure $P_A$ and on the childhood human capital $H_C$, where $\partial f_A/\partial P_A < 0$, and $\partial f_A/\partial H_C > 0$.

$$H_A = f_A(P_A, H_C) \tag{3}$$

Equations (1)-(3) suggest that the impact of fetal pollution exposure on childhood and adulthood human capital relies on both the direct effects of exposure and the transmission of those effects through parental investments. These two pathways can be demonstrated by taking the derivative of equations (2) and (3) with respect to $P_F$:

$$\frac{dH_C}{dP_F} = \frac{\partial f_C}{\partial H_F}\frac{\partial f_F}{\partial P_F} + \frac{\partial f_C}{\partial I_C}\frac{\partial I_C}{\partial H_F}\frac{\partial f_F}{\partial P_F} \tag{4}$$

$$\frac{dH_A}{dP_F} = \frac{\partial f_A}{\partial H_C}\frac{dH_C}{dP_F} = \frac{\partial f_A}{\partial H_C}\frac{\partial f_C}{\partial H_F}\frac{\partial f_F}{\partial P_F} + \frac{\partial f_A}{\partial H_C}\frac{\partial f_C}{\partial I_C}\frac{\partial I_C}{\partial H_F}\frac{\partial f_F}{\partial P_F} \tag{5}$$

In equations (4) and (5), the first term represents the direct effect of fetal exposure to air pollution on human capital, which is negative. It signifies the cumulative impact of air pollution on the development of human capital. The second term represents the indirect effect mediated by parental investments. Its sign is determined by $\partial I_C/\partial H_F$. A negative derivative $\partial I_C/\partial H_F$, which indicates compensatory parental investment, can be interpreted as families' preference to allocate more resources to children with lower endowments at birth. In this scenario, the second term is positive, and the overall effect is attenuated. By contrast, a positive derivative $\partial I_C/\partial H_F$, which suggests reinforcing parental investment, implies that parents invest less in the relatively disadvantaged child. In this setting, the second term is negative, and the total effect becomes more negative.

In sum, a change in fetal pollution exposure $P_F$ affects human capital endowment at birth $H_F$. This shock, in turn, affects long-run human capital through two channels: a direct effect of fetal exposure to air pollution on human capital, and an indirect effect mediated by changes to family investments. The goal of the rest of the paper is to deliver estimates of $dH_C/dP_F$ and $dH_A/dP_F$, and analyze mechanisms that help distinguish between direct effects and indirect effects mediated by parental investments.

# 3 Data

We combine three datasets that collect information on cognitive test scores along with demographic variables, air pollution, and other weather measures.

## 3.1 Cognition data

Data on cognitive test scores are obtained from the China Family Panel Studies (CFPS), a nationally representative biennial longitudinal household survey of Chinese families and individuals. CFPS is funded by Peking University and carried out by the university's Institute of Social Science Survey[7]. We mainly rely on CFPS 2010 as it is the only wave that reveals the birthplace information for each respondent. The cognitive ability module in the

[7] The survey uses multistage probability proportional to size sampling with implicit stratification to represent Chinese society better. The 2010 CFPS baseline sample is drawn through three stages (i.e., county, village, and household) from 25 provinces. The 162 randomly chosen counties largely represent Chinese society (Xie and Hu, 2014).

questionnaire contains 24 mathematics questions and 34 word-recognition questions. All these questions are obtained from standard textbooks and are sorted in ascending order of difficulty. The starting question depends on the respondent's education level[8]. The test ends when the individual incorrectly answers three questions in succession. The final test score is defined as the rank of the hardest question a respondent can answer correctly. If the respondent fails to answer any question, the score is assigned as the rank of the starting question minus one[9]. Only individuals above age 10 are required to take the tests. The cognitive test scores along with demographic variables are linked to air pollution and meteorological data based on the unique birth city identifier and the birth year and month information.

## 3.2 Air pollution data

The concentration of PM2.5 is calculated from the satellite-based Aerosol Optical Depth (AOD) data following the formula provided by Buchard et al. (2016). The AOD data are drawn from the product M2T1NXAER version 5.12.4 from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) released by the U.S. National Aeronautics and Space Administration (NASA). The data are available for each $0.5° \times 0.625°$(around 50 km $\times$ 60 km) grid at the hourly level since 1980. We aggregate all the grids within each city and calculate their mean values. We then average the data to a monthly level for each city. Figure A1 displays the spatial distribution of mean PM2.5 at the city level during 1980-2000. This dataset has been widely used in previous studies (Deschenes et al., 2020; Fu et al., 2021; Chen et al., 2022), and validated with air pollution data from

[8]Specifically, those whose education level is primary school or below start with the 1st question; those who attended middle school begin with the 9th question in the verbal test and the 13th question in the math test; and those who finished high school or above start with the 21st question in the verbal test and the 19th question in the math test.

[9]For example, a respondent with a middle school education begins with the 9th question in the verbal test. If the hardest question one can correctly answer is the 14th question, then the verbal test score would be 14. However, if one fails the 9th, 10th, and 11th questions consecutively, the verbal test score would be 8. Since the respondents did not know the testing rules prior to the interviews, there should be no incentive to manipulate test performance on purpose.

ground-based monitoring stations in China (Chen et al., 2022).[10] We do not use ground-based pollution data for they only cover a few cities before 2012 and report the Air Pollution Index (API) instead of concentrations of specific air pollutants.

## 3.3 Weather data

The weather data are provided by the China National Meteorological Data Service Center (CMDC) under the National Meteorological Information Center of China. The dataset contains daily weather records of 824 monitoring stations along with their longitudes and latitudes in China. The weather measures include temperature, precipitation, wind speed, wind speed direction, sunshine duration, and relative humidity. To merge the birth cities with weather readings, we calculate the mean values of all the monitoring stations within each city. To account for possible non-linear effects of weather controls, we divide the spectrum of temperatures into 10 bins and calculate the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C, 16-20 °C, 20-24 °C, 24-28 °C, and >28 °C) at the city-monthly level. For other weather measures, we use the monthly mean values with their quadratic terms for each city.

As the air pollution data are available after 1980 and only interviewees older than 10 years old are required to take the cognition tests, the final dataset includes 9,038 respondents born between 1980 and 2000. Table 1 provides summary statistics of key variables for the full sample, as well as the female and male subsamples, respectively. During our sample period, the 9-month mean exposure to PM2.5 exceeded 22 $\mu g/m^3$, which is more than four times the annual limit recommended by the WHO.[11] Figure A2 displays the time trend of monthly mean PM2.5 during 1980-2000.

[10] Please see online appendix of Chen et al. (2022) for a comprehensive comparison between AOD-based and station-based pollution data.

[11] According to the 2021 WHO Air Quality Guidelines, the recommended annual limit for PM2.5 is 5 $\mu g/m^3$. Source: https://www.who.int/news-room/feature-stories/detail/what-are-the-who-air-quality-guidelines.

# 4 Empirical Strategy

## 4.1 OLS estimation

We use equation (6) to estimate the impact of prenatal exposure to air pollution on cognitive performance:

$$score_{ijym} = \beta_0 + \beta_1 PM2.5^G_{jym} + \beta_2 X_{ijym} + \beta_3 W_{ijym} + \omega_j + \gamma_y + \tau_m + \varepsilon_{ijym}, \tag{6}$$

$$PM2.5^G_{jym} = \frac{1}{9} \sum_{t=ym-8}^{ym} PM2.5_{jt}, \tag{7}$$

where the outcome variable $score_{ijym}$ is the standardized verbal or math test scores for individual $i$ born in city $j$ in month $m$ of year $y$. $PM2.5^G_{jym}$ denotes the average PM2.5 concentration level during the full gestational age (the past 9 months before birth) as calculated by equation (7). $X_{ijym}$ represents demographic controls, including gender, maternal age, and the mother's education years. $W_{ijym}$ contains a set of weather variables, including the total number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration and mean relative humidity with their square terms during the gestational period. $\omega_j$ indicates the birth city fixed effect; $\gamma_y$ and $\tau_m$ denote the birth year and month fixed effects. The identification is from the monthly variation in PM2.5 pollution within each city after controlling for weather characteristics, annual shocks, and common seasonality effects. As a robustness check, we further add birth year-by-month FE, birth city-by-year FE, and birth city-by-month FE in equation (6). $\varepsilon_{ijym}$ is the error term. Robust standard errors are clustered at the birth city level.[12] A robustness check with two-way clustering at the birth city and year-season levels is also performed.

[12]The respondents were born in 767 counties across 214 cities, resulting in 214 clusters.

## 4.2 IV estimation

OLS estimates of equation (6) are prone to bias for the following two reasons. First, time-varying omitted variables that correlate with PM2.5 pollution and cognitive test scores may bias the estimates despite the rich control variables and fixed effects included in the specifications. For example, local industrial development is correlated with the pollution level and also related to the outcome variables since developed industries may offer more outside opportunities for school-aged kids. They may be lured to drop out of school to seek higher short-term income, which results in lower cognitive abilities. Besides, Tiebout sorting (Tiebout, 1956), through which people choose residential locations based on environmental quality, is likely to confound estimates. Second, there exist measurement errors in the mean PM2.5 readings at the city level matched to each respondent, because it is unknown where exactly the respondent lived in their birth city. Therefore, we deal with the omitted variable issues and measurement errors by constructing IVs following a similar procedure employed by Wang et al. (2022).

PM2.5 could be easily transported from the nearby upwind cities to the focal city by wind (Zhang et al., 2018a; Chen et al., 2020). For each focal city $j$ on month $m$, day $d$ of year $y$, we construct the $P_{j,ymd}$ as a weighted average of the PM2.5 levels of all the nearby upwind cities within 50-200 km from city $f$ using equation (8). We omit cities less than 50 km from the focal city to alleviate concerns of endogeneity risk.

$$P_{j,ymd} = \sum_{n:\ within\ 50-200\ km\ of\ j,\ \cos\theta_{jn,ymd}>0} \omega_{jn,ymd} \times PM2.5_{n,ymd}, \tag{8}$$

$$\omega_{jn,ymd} = \frac{\frac{\cos(\theta_{jn,ymd})}{distance_{jn}} \times \mathbb{1}(\cos\theta_{jn,ymd} > 0)}{\sum_{k:\ within\ 50-200\ km\ of\ j} \frac{\cos(\theta_{jk,ymd})}{distance_{jk}} \times \mathbb{1}(\cos\theta_{jk,ymd} > 0)}, \tag{9}$$

$$IV_{j,ymd} = \sum_{t=ymd-6}^{ymd} P_{j,t}. \tag{10}$$

$PM2.5_{n,ymd}$ is the PM2.5 level of nearby city $n$ on month $m$, day $d$ of year $y$. We only keep the nearby cities in the upwind directions with $\cos\theta_{jn,ymd} > 0$, where $\theta_{jn,ymd}$ is the angle between the vector $\vec{nj}$ from the nearby city $n$ to the focal city $j$ and the prevailing wind direction on month $m$, day $d$ of year $y$. Figure A3 provides a graphical illustration of the aforementioned parameters. According to equation (9), the weight $\omega_{jn,ymd}$ is larger if the distance between city $n$ and $j$ ($distance_{jn}$) is smaller and the angle $\theta_{jn,ymd}$ is closer to zero. Furthermore, considering that the transport of air pollutants takes time, we incorporate the impact of PM2.5 pollution from nearby cities in the preceding week. Thus, the IV for local PM2.5 pollution, denoted as $IV_{j,ymd}$, is defined in equation (10). After obtaining the $IV_{j,ymd}$ at the daily level, we aggregate it to the city-monthly level $IV_{jym}$. We then calculate $IV^G_{jym}$ following the same way as PM2.5 in equation (7).

We use $IV^G_{jym}$ to instrument for $PM2.5^G_{jym}$ in equation (6) and estimate the equation using two-stage least square (2SLS) method, where the first stage specification is:

$$PM2.5^G_{jym} = \beta_0 + \beta_1 IV^G_{jym} + \beta_2 X_{ijym} + \beta_3 W_{ijym} + \omega_j + \gamma_y + \tau_m + \varepsilon_{ijym}. \tag{11}$$

We demonstrate the validity of the IVs in regard to the exclusion and relevance assumptions. The relevance assumption is reassured by the strong first-stage regression results shown in Table 2. For the exclusion restriction, since changes in the wind direction are a natural phenomenon, pollution transmitted from the nearby upwind cities to the focal is uncorrelated with the unobservables in the focal city. Similar IV strategies have been widely adopted in recent studies (Bayer et al., 2009; Zheng et al., 2019; Chen et al., 2021; Barwick et al., 2021; Fu et al., 2022). After controlling for meteorological variables, as well as spatial and temporal fixed effects, our identification assumption is that the transported air pollutants from nearby cities could only affect the cognitive performance of people born in the focal city by raising air pollutant concentration levels. See Section 5.2 for additional robustness checks on the IV construction method.

# 5 Results

## 5.1 Baseline results

Table 2 displays the results for the impact of fetal exposure to PM2.5 on verbal and math test scores. All the regressions control for demographic controls, weather controls, birth city fixed effects, as well as birth year and month fixed effects. Columns (1) and (2) of Table 2 first report the OLS estimates. The results show that the mean PM2.5 level during pregnancy is negatively correlated with both verbal and math test scores. Specifically, a one SD increase in PM2.5 (6.719 $\mu g/m^3$) during pregnancy leads to a reduction in verbal and math test scores by 0.813 (0.108 SD) and 0.867 (0.153 SD), respectively.[13] Columns (3) of Table 2 presents the first-stage results of our IV estimation. The constructed IV is significantly and positively correlated with PM2.5. Overall, we find a strong first-stage relationship. The Kleibergen–Paap (KP) F-statistics are well above the Stock–Yogo critical value, which reassures the validity of the IVs. Columns (4) and (5) of Table 2 report the IV estimates. Columns (1) and (2) indicate that a one SD increase in fetal exposure to PM2.5 during the gestational period is associated with a reduction in verbal and math test scores by 0.921 (0.122 SD) and 0.968 (0.170 SD), respectively.

The magnitudes of the coefficients on PM2.5 in the IV estimates are greater than those in the OLS estimates, which is common in the literature (Barwick et al., 2021; Wang et al., 2022). Two possible reasons exist for this downward bias. First, some omitted variables, such as residential sorting, are correlated with air pollution. Second, measurement errors in PM2.5 could lead to attenuation bias. Given the potential endogeneity in the OLS regressions, we will focus on the interpretation of 2SLS results in the remaining sections.

We compare the magnitude of our estimates with other similar studies that also examine the effect of early-life exposure to air pollution on cognitive performance. The relevant studies are summarized in Table 3. To facilitate comparisons across studies, we report the

[13] Note the SD of verbal and math test scores are 7.527 and 5.677, respectively.

effect sizes in SD change of test scores per one SD higher in air pollutants. As for our estimates, a one SD increase in fetal exposure to PM2.5 is associated with a reduction in verbal and math test scores by 0.122 SD and 0.170 SD, respectively. Meanwhile, Sanders (2012) observes that a one SD increase in TSPs (7.27 $\mu g/m^3$) in the student's year of birth correlates with a 0.06 SD decline in high school scores. Bharadwaj et al. (2017) report that a one SD increase in PM10 (29.24 $\mu g/m^3$) during the third trimester is associated with a 0.029 SD reduction in math scores and a 0.037 SD reduction in language scores. While our estimate is marginally higher, it reflects a comparable magnitude to their findings, given that we employ IV estimates.

## 5.2 Robustness checks

In this section, we conduct a set of tests to check the robustness of our main results. To begin with, We employ alternative IV construction methods. First, we exclude nearby cities within 100 km instead of 50 km from the focal cities during the construction of IV to further address concerns of endogeneity. Second, following Rangel and Vogl (2019), we restrict the angle between the vector $\vec{nj}$ and the prevailing wind direction of the focal city $c$ ($\theta_{jn,ymd}$) to 60°and 45°, respectively. Third, following Chen et al. (2021), as higher wind speeds in focal cities would transport PM2.5 from nearby cities more quickly, we add wind speed to the weight function as shown in equation (12). The estimation results are displayed in Table A1. Overall, the results remain largely unchanged, which establishes the robustness of our estimates across different IV construction methods.

$$\omega_{jn,ymd} = \frac{\frac{\cos(\theta_{jn,ymd})}{distance_{jn}} \times \mathbb{1}(\cos\theta_{jn,ymd} > 0) \times windspeed_{j,ymd}}{\sum_{k:\ within\ 50-200\ km\ of\ j} \frac{\cos(\theta_{jk,ymd})}{distance_{jk}} \times \mathbb{1}(\cos\theta_{jk,ymd} > 0) \times windspeed_{k,ymd}} \tag{12}$$

Another problem that may bias our estimated results is that air pollution may affect migratory choices (Chen et al., 2022). It is possible that individuals who have experienced pollution shocks may decide to relocate to other cities.[14] To alleviate this concern, we exclude migrants from our sample. We employ two methods to identify migrants: (1) individuals who did not reside in the same city at birth and when they were three years old, and (2) individuals who did not reside in the same city at birth and during the survey period. Columns (1) through (4) of Table A2 indicate that migration, and thus location sorting, is unlikely to significantly bias our estimates.

It is also plausible that exposure to air pollution after birth, which may be associated with fetal exposure, could affect long-term cognitive performance. While our IV strategy, utilizing prenatal wind direction, effectively mitigates the influence of postnatal air pollution, we further refine our analysis by restricting the sample to individuals who resided in the same city at birth and during the survey period. Subsequently, we calculate the monthly mean PM2.5 level from the second month after birth to the month of interview for each respondent, incorporating it as a control variable.[15] The results are displayed in columns (5) and (6) of Table A2. As expected, the magnitudes and significance levels of prenatal PM2.5 exposure remain largely unchanged compared to our baseline IV estimates. In addition, we conduct a placebo test to further support our identifying assumptions. We forward the respondent's date of birth by one year and match the PM2.5 exposure, and construct IVs based on this "false birth date." The preconception exposure to PM2.5 should not affect cognitive performance unless the identified effect is driven by unobserved confounding factors or trends. In line with our expectations, the findings presented in columns (7) and (8) of Table A2 demonstrate that exposure to PM2.5 before conception has no significant impact on test scores, and the magnitudes of the coefficients are also small.

Our baseline results are also robust to a wide variety of specification checks. First, one

[14] Due to data limitation, it is impossible to track migration behavior *in utero*, which may introduce bias into the environment-birthplace matching process. However, this migration cohort should constitute only a small proportion of the whole sample. In the sampling period (1980-2000), intercity migration was rare due to the strict *hukou* policy (e.g., Meng, 2012; Fan, 2019). Moreover, medical insurance in China was tightly bonded with *hukou*, adding more difficulty for pregnant women to relocate to other cities (Müller, 2016; Ngai et al., 2019).

[15] We instrument after-birth PM2.5 exposure using wind directions, akin to our approach for instrumenting fetal air pollution exposure.

may worry that some demographic controls are endogenous, potentially resulting in biased estimates of the variables of interest. For instance, maternal age at childbirth could be influenced by selection into fertility in response to air quality concerns. Columns (1)-(2) of Table A3 show that our results are robust to excluding demographic controls using the same regression. Second, we add birth year-by-month fixed effects to the regressions in columns (3) and (4). Our main findings remain unchanged. Third, columns (5) and (6) show that the main estimation results still hold after controlling for the birth city-by-year and city-by-month fixed effects, although the magnitudes of the estimates are exacerbated. Furthermore, in columns (7) and (8) standard errors are two-way clustered at the birth city and birth year-season levels (Cameron et al., 2011), which allows for serial correlation within each birth city and correlation across all birth cities in the same birth year-season. The standard errors are slightly larger compared to Table 2, but the significance level remains. These alternative fixed effects and two-way clustering further confirm the robustness of our results.

### 5.3 Heterogeneous effects

We first examine the heterogeneous effects of PM2.5 exposure by gender. As shown in Panel A of Table 4, the coefficients on the PM2.5 level are statistically significant for females taking both tests and males taking the math test. For the math test, both females and males are affected, but the effect on females is larger and more significant. Therefore, our results suggest that females are more vulnerable to fetal PM2.5 exposure compared with their male counterparts.

Our identified stronger effect for females compared with males seems to contradict the prevailing "fragile males" hypothesis, which reveals that male fetuses are more vulnerable to detrimental influences *in utero* than female fetuses. The "fragile males" hypothesis has been widely documented in the existing literature (e.g., Kraemer, 2000; Eriksson et al., 2010; Currie and Schwandt, 2016; Almond and Mazumder, 2011; Ebenstein et al., 2016). We will investigate potential channels to solve this puzzle in the next section.

Moreover, we also test the heterogeneous effect by age cohort, and socioeconomic status (SES). As revealed in Panel B of Tables 4, the negative effect of prenatal exposure to air pollution on cognitive performance becomes more prominent when people get older. To determine the SES of survey respondents, we categorize them into two groups based on their mothers' education level. Specifically, respondents whose mothers completed less than 9 years of education are assigned to the low SES group, while those whose mothers completed more than 9 years are assigned to the high SES group. The results in Panel C of Table 4 show that respondents with low SES, a measure of resource constraint, are more vulnerable to prenatal PM2.5 exposure.

# 6 Mechanisms

In this section, we test several potential mechanisms that could explain the more pronounced effect of fetal PM2.5 exposure on females compared to males. The first channel belongs to the biological pathway, specifically mortality selection, while the others are associated with the socioeconomic pathway, including selection into motherhood, strategic fertility decisions, and gender-specific parental investment.

## 6.1 Mortality selection

Negative shocks may increase fetal mortality directly through a biological effect, also known as the culling effect. Meanwhile, the scarring effect may prevail when *in utero* adverse environment is not strong enough to cause fetal death but impacts surviving newborns. If the culling effect dominates the scarring effect for males, weak male fetuses are more likely to be selected out by PM2.5 exposure. This *in utero* mortality selection thus leads the surviving boys to be inherently healthier and perform better in later life.

We first test this channel by looking at the effect of prenatal exposure to air pollution during the gestational period on being a male using the CFPS data. If male fetuses are at greater risk of mortality compared to female fetuses, we would identify a significant negative effect on the individuals being male. Results in column (1) of Table 5 demonstrate that fetal exposure to air pollution has no distinguishable effects on the gender of respondents, which largely rules out the significance of mortality selection.

To address concerns regarding the representativeness of the sex ratio in the CFPS data for the Chinese population, we calculate the sex ratio of individuals born between 1980 and 2010 within each birth-city-year-month cell. These calculations are based on the 2000 and 2010 Population Census Data of China. As presented in column (2) of Table 5, the findings indicate that fetal exposure to PM2.5 has minimal effects on the sex ratio, thereby ruling out the possibility of mortality selection.

## 6.2 Selection into motherhood and fertility decisions

Mothers who are aware of the risks associated with air pollution may choose to avoid exposure or plan their pregnancies during periods of better air quality. This awareness is likely correlated with the mother's education level and knowledge of air pollution. Additionally, exposure to air pollution can influence a couple's decision regarding subsequent pregnancies or the spacing between pregnancies, which may be associated with the gender of the previous child. If this happens, our findings could be susceptible to bias stemming from these selection processes and strategic pregnancy decisions. We test these potential channels by examining whether air pollution is associated with mother's education level, age at birth, as well as birth spacing and the decision to have another child by the gender of the previous child. Relevant results are shown in columns (3)-(8) of Table 5. We observe no significant effect of air pollution on any of these channels, suggesting that our results are not influenced by selection into motherhood or strategic fertility decisions.

## 6.3 Gender-specific parental investment

In this section, we test the pathway related to gender-specific parental investment. We first examine the heterogeneous effects based on the number of siblings and their gender composition. Table 6 reports the IV results. Panel A refers to the females while Panel B corresponds to the males. For each outcome, we study the effect of PM2.5 for four subsamples, namely, the only child, having siblings, having brothers, and having only sisters.

The IV results suggest that females with siblings are more vulnerable to the detrimental effects of PM2.5 exposure on both verbal and math abilities, especially when they have brothers. Specifically, for a girl with siblings, an additional SD increase in fetal PM2.5 exposure (6.750 $\mu g/m^3$) on average reduces her verbal and math test scores by 1.816 (0.239 SD) and 1.991 (0.346 SD), respectively.[16] Even worse, the condition deteriorates when she has brothers in the family, where the reduction becomes 2.241 (0.295 SD) and 2.241 (0.390 SD) for verbal and math test scores, respectively. In contrast, for males, the adverse effects are not statistically significant for either verbal or math test scores.

A possible explanation could be the prevailing son preference in China. In credit-constrained families with multiple children, parents tend to allocate more resources to their sons to compensate for the damage caused by prenatal PM2.5 exposure.[17] Girls with fewer resources within the household and limited access to education, therefore, develop worse cognitive abilities than boys when exposed to negative shocks *in utero*. All samples for this study were born after 1980, when China's one-child policy (OCP) was initiated, which may help partially explain the insignificant effects for those who are the only child in the family. Under OCP's restrictive fertility policy stipulation, the only child (most common in urban areas; for rural areas, parents could have a second child if the firstborn was a girl) would be

[16] Note the SD of verbal and math test scores for the female subsample are 7.597 and 5.753, respectively.

[17] The US Embassy began releasing the PM2.5 concentration levels in Beijing via Twitter in March 2008. Government and public awareness of PM2.5 significantly increased around 2013, following several severe haze and pollution events (Liu et al., 2022). Thus, it is unlikely that our respondents and their parents were aware of the health consequences of particulate matter during our sample period (1980-2010). The health consequences are more likely to have been inferred by parents through observing their children's health and intellectual development outcomes.

more valued and better attended by parents.

In addition to the heterogeneous effects of sibling gender composition, we further test two direct channels that could lead to the observed phenomenon. The first is that more fetal exposure to PM2.5 leads people, especially women, to stay fewer years in school, thus receiving less cognitive training that results in poorer cognitive performance. The second channel is that families with multiple children may invest differently in their offspring based on personal preference. We can observe this preference as revealed by both educational and health investments. In our context, it is possible that their female descendants who were exposed to more PM2.5 *in utero* were invested less, due to the strong son preference that exists in China (Wang, 2005; Lei et al., 2017).

### 6.3.1 Educational attainment

In this section, we examine the impact of fetal PM2.5 exposure on educational attainment by gender, excluding individuals not completing education. As illustrated in columns (1)-(2) of Table 7, the coefficients on PM2.5 levels are statistically significant and negative for females, but insignificant for males. Specifically, a one SD increase in PM2.5 exposure (6.750 $\mu g/m^3$) during pregnancy results in a reduction of 1.060 years of education in later life for females. For the entire sample, we introduce a dummy variable to denote age-appropriate grade completion.[18] As displayed in columns (3)-(4) of Table 7, the impact is more pronounced among females. Precisely, a one SD increase in PM2.5 exposure during pregnancy reduces the probability of age-appropriate grade completion by 6.08 percentage points for females, *ceteris paribus*.

We also test the heterogeneous effects of sibling gender composition on years of education and age-appropriate grade completion. The results are presented in Tables A4 and A5, respectively. These estimates exhibit a similar pattern to those observed in Table 6 regard-

[18] For individuals aged between 10 and 20 years old, we define age-appropriate grade completion as the difference between age and years of education being less than 8 (implying that children aged 8 must have completed at least the first grade). For those aged above 20 years old, we define age-appropriate grade completion as having completed high school (12th grade).

ing test scores. According to the results, the adverse effects of air pollution exposure are more pronounced among females with siblings, with those having brothers experiencing the greatest impact. Specifically, for a girl with brothers, a one SD increase in prenatal PM2.5 exposure, on average, reduces her years of education by 1.532 years and decreases the probability of age-appropriate grade completion by 14.18 percentage points. These findings offer further support to gendered consequences of fetal exposure to PM2.5 on cognitive abilities.

### 6.3.2 Human capital investment by families

The other channel more closely relates to son preference involves imbalanced human capital investment within the household based on the gender of the children. Deeply rooted in the conventions, sons in China are expected to inherit family names, provide economic returns, and care for elderly parents. Daughters, on the other hand, are expected to marry out and become part of other families (e.g., Wei and Zhang, 2011). Parents may, therefore, invest more time and money in boys' human capital development.

We explore this channel by examining two key aspects of family human capital investment: educational investment and health investment.[19] The results related to educational investment are displayed in columns (5)-(8) of Table 7. Specifically, we investigate the impact of fetal exposure to air pollution on family education spending and the time family members spend helping children with homework (measured in hours per week) across both male and female subsamples. Although we do not observe any gender difference in family education spending, we observe a noteworthy reduction in the time parents devote to helping their child with homework by 17.6% for females per one SD increase in PM2.5 exposure (6.750 $\mu g/m^3$).[20]

[19] The CFPS collects data on family human capital investment only for children under the age of 16.

[20] During our study period (1980-2000), "extracurricular tutoring," referring to training classes held outside of regular school hours to enhance academic performance or develop specialized skills, was not prevalent in China. Only 14.7% of children participated in extracurricular tutoring within our sample. This limited participation could be a factor contributing to the absence of a significant difference in family education spending based on gender, especially considering similar expenditures on compulsory education in schools during that time frame.

We further look at the heterogeneous effects on time spent helping children with homework by sibling gender composition. Table A6 displays a similar pattern as in the educational attainment part discussed above. The IV results indicate that the adverse effects of prenatal exposure to PM2.5 on family assistance time with homework are only statistically significant for females, especially those with siblings. In response to fetal exposure to air pollution, parents may allocate more resources to their sons as compensation. Girls, in turn, could receive less investments when they have brothers.

Since health and educational attainment are both key dimensions of individual capacity, disparities in early-life health investment within households may also contribute to gender differences in cognitive abilities later in life. Intriguingly, parental responses could differ across these two dimensions. For example, it could be that parents might prefer to compensate in health investment but reinforce in educational investment (Yi et al., 2015). In Table A7, we find that prenatal exposure to PM2.5 has little effect on birth health or child health. In Table 8, we further examine the impact of fetal exposure to air pollution on health investment. Specifically, we investigate the effect on the duration of breastfeeding, medical expenses, and health insurance coverage for both male and female subgroups. However, our findings provide little support for this health investment channel.

# 7 Conclusion

In this paper, we examine the long-term impact of prenatal exposure to PM2.5 on cognitive performance measured by standardized verbal and math test scores, using a nationally representative longitudinal survey in China. To address potential endogeneity in PM2.5, we construct IVs using the local wind direction and the pollution level of nearby upwind cities. Our IV estimates suggest that a one SD increase in fetal PM2.5 exposure leads to a decline in verbal and math test scores by 0.122 SD and 0.170 SD, respectively. We identify strong heterogeneity by gender. Females are more affected than males, which contradicts the “fragile males” hypothesis documented in the literature. We examine the effect of the siblings’ gender composition and find that females with siblings are more vulnerable to the detrimental effects of PM2.5 exposure on both verbal and math abilities, especially when they have brothers. Specifically, for a girl with brothers in the family, a one SD increase in prenatal PM2.5 exposure is associated with a reduction in verbal and math test scores by 0.295 SD and 0.390 SD, respectively.

To explain this gendered pattern, we rule out several competing channels, including mortality selection, selection into motherhood, fertility decisions, and gender-specific health investments by families. Our findings suggest that gender-biased human capital investment by families tends to amplify the adverse effects of early-life shocks on cognitive abilities for girls while mitigating these effects for boys. Specifically, when exposed to the same level of fetal PM2.5, females receive less assistance with homework from family members and achieve lower levels of education compared to their male counterparts. This impact is particularly pronounced for females who have siblings, especially those with brothers.

In evaluating the long-term impacts of exposure to air pollution, our study offers a perspective on cognitive performance and educational attainment that may be applied to the contexts of other developing countries. Our findings suggest that the disadvantage resulting from negative shocks *in utero* could be mitigated by increasing human capital investment in later life, which leaves opportunities for remedial policies, such as healthcare subsidies for pregnant women and enforcing compulsory education. The differentiated investments between boys and girls within households due to son preference would enlarge the gender gap. Therefore, with the continuing urbanization in China and its transition from the OCP to the three-child policy, it is important to reevaluate the effects in the years to come.

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Table 1: Summary statistics

| VARIABLES | All ($N = 9,038$) | | Female ($N = 4,463$) | | Male ($N = 4,575$) | |
|---|---|---|---|---|---|---|
| | mean | SD | mean | SD | mean | SD |
| Verbal test | 23.749 | 7.527 | 24.021 | 7.597 | 23.470 | 7.445 |
| Math test | 13.692 | 5.677 | 13.518 | 5.753 | 13.870 | 5.592 |
| PM2.5 level | 22.444 | 6.719 | 22.461 | 6.750 | 22.427 | 6.687 |
| Gender | 0.494 | 0.500 | 0.000 | 0.000 | 1.000 | 0.000 |
| Maternal age | 25.590 | 4.438 | 25.504 | 4.395 | 25.677 | 4.480 |
| Mother's education years | 5.514 | 4.585 | 5.594 | 4.560 | 5.432 | 4.610 |
| Temperature bins | | | | | | |
| <-4 °C | 17.876 | 30.727 | 18.188 | 30.995 | 17.557 | 30.450 |
| -4-0 °C | 14.241 | 15.600 | 14.697 | 15.823 | 13.774 | 15.355 |
| 0-4 °C | 21.199 | 16.747 | 21.458 | 16.778 | 20.933 | 16.712 |
| 4-8 °C | 25.797 | 16.362 | 25.788 | 16.113 | 25.806 | 16.615 |
| 8-12 °C | 27.740 | 13.941 | 27.775 | 13.645 | 27.703 | 14.240 |
| 12-16 °C | 32.574 | 14.340 | 32.576 | 14.530 | 32.573 | 14.143 |
| 16-20 °C | 38.635 | 17.089 | 38.310 | 16.797 | 38.967 | 17.379 |
| 20-24 °C | 42.817 | 21.209 | 42.547 | 21.699 | 43.093 | 20.694 |
| 24-28 °C | 38.258 | 30.017 | 37.852 | 30.050 | 38.674 | 29.980 |
| >28 °C | 14.818 | 19.871 | 14.768 | 19.833 | 14.870 | 19.912 |
| Precipitation | 2.620 | 1.615 | 2.605 | 1.624 | 2.635 | 1.606 |
| Wind speed | 2.300 | 0.762 | 2.296 | 0.764 | 2.304 | 0.760 |
| Relative humidity | 70.543 | 8.715 | 70.400 | 8.835 | 70.690 | 8.588 |
| Sunshine duration | 5.715 | 1.293 | 5.725 | 1.300 | 5.704 | 1.286 |

Table 2: Baseline results

| | OLS | | first stage | 2SLS | |
|---|---|---|---|---|---|
| VARIABLES | verbal test | math test | PM2.5 level | verbal test | math test |
| | (1) | (2) | (3) | (4) | (5) |
| PM2.5 level | -0.121*** | -0.129*** | | -0.137** | -0.144*** |
| | (0.046) | (0.039) | | (0.059) | (0.051) |
| PM2.5 IV | | | 0.131*** | | |
| | | | (0.005) | | |
| Observations | 9,038 | 9,038 | 9,038 | 9,038 | 9,038 |
| KP first-stage F-statistic | | | | 720.6 | 720.6 |
| Demographic controls | Y | Y | Y | Y | Y |
| Weather controls | Y | Y | Y | Y | Y |
| Birth city FE | Y | Y | Y | Y | Y |
| Birth year and month FE | Y | Y | Y | Y | Y |

*Notes:* Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table 3: Relevant studies on the effect of early-life exposure to air pollution on cognitive performance

| Study | Region | Years | Outcomes | Pollutants | Effects |
|---|---|---|---|---|---|
| Molina (2021) | Mexico | 2002-2009 (survey year) | Raven's test score, height, years of schooling, annual income | CO, PM10 | A one SD increase in average monthly thermal inversions per trimester (8.2) leads to a 0.106 SD decline in Raven's test scores. |
| Sanders (2012) | Texas, United States | 1979-1985 (birth year) | High school math test scores | TSP | A one SD increase in TSPs (7.27 $\mu g/m^3$) in the student's year of birth is associated with a 0.06 SD decrease in high school scores. |
| Bharadwaj et al. (2017) | Santiago, Chile | 1992-2001 (birth year) | fourth-grade SIMCE test scores | CO, PM10, AQI | A one SD increase in CO (0.93 ppm) in the third trimester is associated with a 0.034 SD reduction in fourth-grade math scores and a 0.040 SD reduction in language scores. A one SD increase in PM10 (29.24 $\mu g/m^3$) in the third trimester is associated with a 0.029 SD reduction in math scores and a 0.037 SD reduction in language scores. |
| Rosales-Rueda and Triyana (2019) | Indonesia | 1997 (exposure year) | Height-for-age, height, lung capacity, cognitive test scores | aerosol index | They find no significant effect of *in utero* exposure to fires on cognitive function as measured by age-adjusted cumulative test scores. |

*Notes:* Our IV estimates indicate that a one SD increase in fetal exposure to PM2.5 during the gestational period is associated with a reduction in verbal and math test scores by 0.122 SD and 0.170 SD, respectively.

Table 4: Heterogeneous effects by gender, age and SES (2SLS)

| Panel A. *Gender* | | | | |
|---|---|---|---|---|
| VARIABLES | verbal test | | math test | |
| | female<br>(1) | male<br>(2) | female<br>(3) | male<br>(4) |
| PM2.5 level | -0.212***<br>(0.078) | -0.037<br>(0.082) | -0.190***<br>(0.070) | -0.090*<br>(0.054) |
| Observations | 4,575 | 4,463 | 4,575 | 4,463 |
| KP first-stage F-statistic | 553.8 | 724.6 | 553.8 | 724.6 |
| **Panel B. *Age*** | | | | |
| VARIABLES | verbal test | | math test | |
| | age10-19<br>(1) | age20-30<br>(2) | age10-19<br>(3) | age20-30<br>(4) |
| PM2.5 level | -0.091<br>(0.067) | -0.216*<br>(0.124) | -0.096*<br>(0.056) | -0.184**<br>(0.092) |
| Observations | 4,809 | 4,229 | 4,809 | 4,229 |
| KP first-stage F-statistic | 440.2 | 767.3 | 440.2 | 767.3 |
| **Panel C. *SES*** | | | | |
| VARIABLES | verbal test | | math test | |
| | low SES<br>(1) | high SES<br>(2) | low SES<br>(3) | high SES<br>(4) |
| PM2.5 level | -0.202**<br>(0.086) | -0.042<br>(0.052) | -0.263***<br>(0.061) | -0.004<br>(0.042) |
| Observations | 5,501 | 3,537 | 5,501 | 3,537 |
| KP first-stage F-statistic | 596.1 | 826.3 | 596.1 | 826.3 |

*Notes:* All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table 5: Mechanism test: mortality selection, selection into motherhood and fertility decisions (2SLS)

| VARIABLES | mortality selection | | selection into motherhood | | fertility decisions | | | |
|---|---|---|---|---|---|---|---|---|
| | CFPS male dummy | population census sex ratio (%) | mother's education years | mother's age at birth | birth spacing | | having another child | |
| | | | | | female | male | female | male |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| PM2.5 level | -0.004 | 0.246 | 0.017 | 0.009 | -0.005 | -0.003 | -0.003 | -0.005 |
| | (0.004) | (0.238) | (0.031) | (0.031) | (0.056) | (0.074) | (0.005) | (0.005) |
| Observations | 9,038 | 107,538 | 9,038 | 9,038 | 2,165 | 1,434 | 4,575 | 4,463 |
| KP first-stage F-statistic | 720.9 | 712.1 | 719.8 | 720.4 | 805.5 | 422.5 | 553.8 | 724.6 |

*Notes:* Columns (1) is regressed at the individual level using the CFPS data. Columns (2) is regressed at the city-year-month level based on the 2000, 2010 Population Census Data of China. All the regressions include weather controls, birth city fixed effects, and birth year and month fixed effects. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. For demographic controls, gender is included in columns (3)-(4); maternal age is included in columns (1), (3) and (5)-(8); mother's education years is included in columns (1), (4) and (5)-(8). Robust standard errors, clustered at the city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table 6: Mechanism test: heterogeneous effect based on the number of siblings and their gender composition (2SLS)

| VARIABLES | verbal test | | | | math test | | | |
|---|---|---|---|---|---|---|---|---|
| | **only child** (1) | **having siblings** (2) | **having brothers** (3) | **having only sisters** (4) | **only child** (5) | **having siblings** (6) | **having brothers** (7) | **having only sisters** (8) |
| Panel A. *Female* | | | | | | | | |
| PM2.5 level | -0.105 | -0.269** | -0.332*** | -0.210 | 0.002 | -0.295*** | -0.332*** | -0.317** |
| | (0.093) | (0.105) | (0.122) | (0.201) | (0.078) | (0.080) | (0.088) | (0.149) |
| Observations | 1,034 | 3,541 | 2,654 | 887 | 1,034 | 3,541 | 2,654 | 887 |
| KP F-statistic | 418.4 | 643.5 | 504.4 | 456.1 | 418.4 | 643.5 | 504.4 | 456.1 |
| Panel B. *Male* | | | | | | | | |
| PM2.5 level | -0.093 | 0.010 | 0.227 | -0.219 | -0.099 | -0.086 | -0.058 | -0.091 |
| | (0.122) | (0.106) | (0.170) | (0.144) | (0.085) | (0.070) | (0.103) | (0.091) |
| Observations | 1,446 | 3,017 | 1,589 | 1,428 | 1,446 | 3,017 | 1,589 | 1,428 |
| KP F-statistic | 593.5 | 456.3 | 306.7 | 529.4 | 593.5 | 456.3 | 306.7 | 529.4 |

*Notes:* All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table 7: Mechanism test: effects of PM2.5 on educational attainment and educational investment (2SLS)

| VARIABLES | educational attainment | | | | educational investment | | | |
|---|---|---|---|---|---|---|---|---|
| | years of education | | age-appropriate grade completion | | time spent helping children with homework (log form) | | family education spending (log form) | |
| | female (1) | male (2) | female (3) | male (4) | female (5) | male (6) | female (7) | male (8) |
| PM2.5 level | -0.157** | 0.054 | -0.009** | -0.002 | -0.026** | 0.006 | -0.002 | 0.059 |
| | (0.073) | (0.070) | (0.005) | (0.004) | (0.012) | (0.016) | (0.023) | (0.039) |
| Observations | 2,244 | 2,085 | 4,575 | 4,463 | 1,529 | 1,548 | 1,529 | 1,548 |
| KP first-stage F-statistic | 472.1 | 864.7 | 553.8 | 724.6 | 364.2 | 266 | 364.2 | 266 |
| Mean of Dep. Var. | 9.467 | 9.730 | 0.660 | 0.684 | 1.869 | 2.233 | 1080 | 1141 |

*Notes:* The sample in columns (1)-(2) only includes individuals with completed education levels. Due to data availability, the sample in columns (5)-(8) only includes children younger than 16. All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table 8: Mechanism test: effects of PM2.5 on health investment (2SLS)

| VARIABLES | duration of breast-feeding (month) | | medical expenses (log form) | | health insurance coverage | |
|---|---|---|---|---|---|---|
| | female (1) | male (2) | female (3) | male (4) | female (5) | male (6) |
| PM2.5 level | 0.056 | -0.106 | -0.065* | -0.071 | 0.008 | -0.003 |
| | (0.111) | (0.181) | (0.036) | (0.056) | (0.007) | (0.009) |
| Observations | 1,430 | 1,466 | 1,529 | 1,548 | 1,528 | 1,548 |
| KP first-stage F-statistic | 338.8 | 269.3 | 364.2 | 266 | 364.3 | 266 |
| Mean of Dep. Var. | 13.48 | 14.67 | 290.3 | 403.1 | 0.677 | 0.714 |

*Notes:*Due to data availability, the sample only includes children younger than 16. All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

# APPENDIX A: Supplementary Figures and Tables

Figure A1: Spatial distribution of PM2.5 ($\mu g/m^3$) at city level during 1980-2000, China

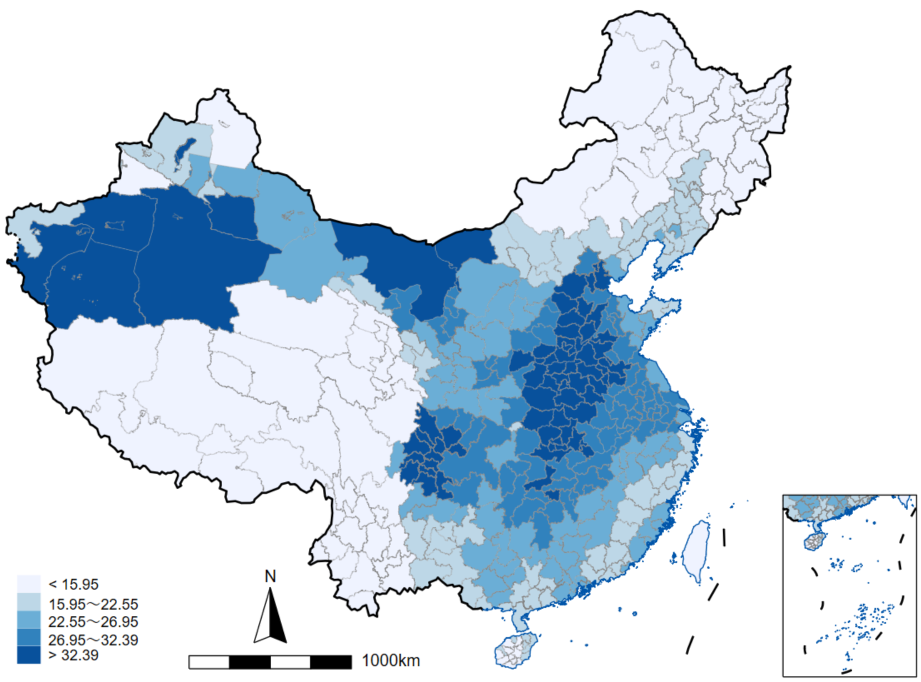


Figure A2: Monthly mean PM2.5 (μg/m$^3$) during 1980-2000, China

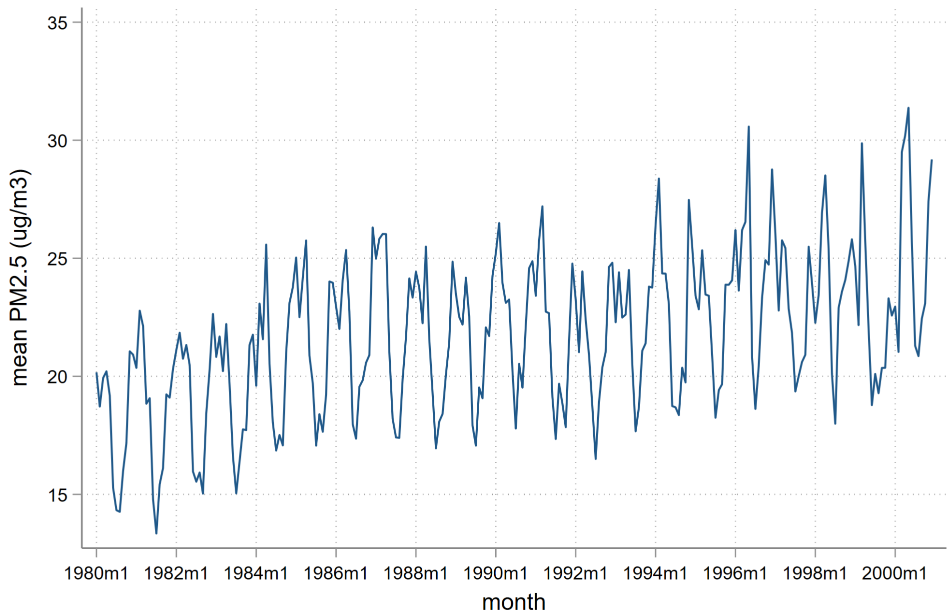
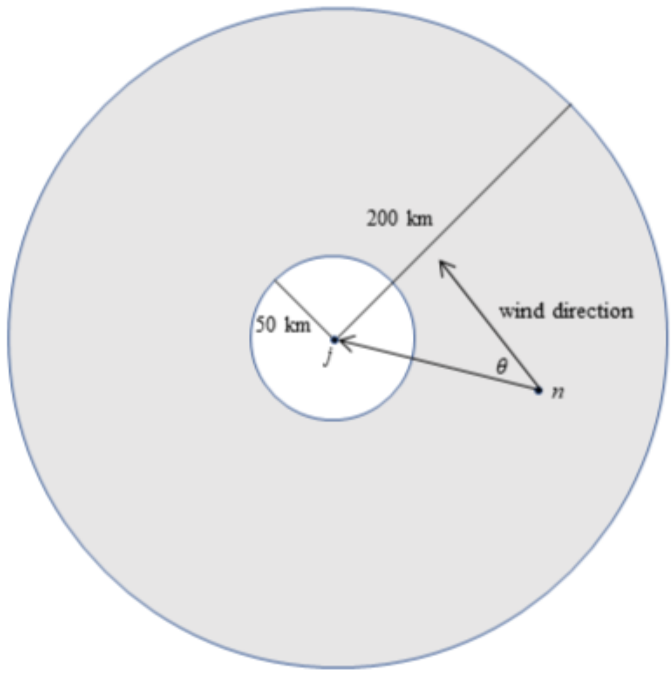


Figure A3: Illustration of the upwind instrumental variable strategy




*Note:* The figure illustrates the transported air pollution from a nearby upwind city $n$ to the focal city $j$. $\theta$ denotes the angle between the vector $\vec{nj}$ and the wind direction.

Table A1: Robustness checks for alternative IV constructions (2SLS)

| | 100 km range | | 60 degree | | 45 degree | | wind speed | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | verbal test (1) | math test (2) | verbal test (3) | math test (4) | verbal test (5) | math test (6) | verbal test (7) | math test (8) |
| PM2.5 level | -0.138** | -0.145*** | -0.142** | -0.144*** | -0.110* | -0.129*** | -0.137** | -0.144*** |
| | (0.059) | (0.051) | (0.060) | (0.050) | (0.058) | (0.044) | (0.059) | (0.051) |
| Observations | 9,038 | 9,038 | 8,990 | 8,990 | 8,938 | 8,938 | 9,038 | 9,038 |
| KP first-stage F-statistic | 668.1 | 668.1 | 916.3 | 916.3 | 723.8 | 723.8 | 720.6 | 720.6 |

*Notes:* All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table A2: Robustness checks for migration, postnatal exposure and placebo tests (2SLS)

| | excluding migrants at 3 years old | | excluding migrants at the survey year | | including after-birth exposure | | placebo tests | |
|---|---|---|---|---|---|---|---|---|
| VARIABLES | verbal test (1) | math test (2) | verbal test (3) | math test (4) | verbal test (5) | math test (6) | verbal test (7) | math test (8) |
| Fetal PM2.5 level | -0.151** | -0.150*** | -0.157** | -0.164*** | -0.118** | -0.135*** | -0.087 | -0.058 |
| | (0.061) | (0.050) | (0.066) | (0.054) | (0.059) | (0.051) | (0.069) | (0.047) |
| Postnatal PM2.5 level | | | | | -0.348*** | -0.330*** | | |
| | | | | | (0.131) | (0.116) | | |
| Observations | 8,737 | 8,737 | 7,614 | 7,614 | 7,258 | 7,258 | 8,585 | 8,585 |
| KP first-stage F-statistic | 714.2 | 714.2 | 626.6 | 626.6 | 310.1 | 310.1 | 353.5 | 353.5 |

*Notes:* The placebo test is conducted by matching the PM2.5 exposure and the constructed IV from one year ago. All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table A3: Robustness checks for alternative specifications (2SLS)

| VARIABLES | excluding demographic controls | | adding birth year-by-month FE | | adding birth city-by-year and city-by-month FE | | two-way clustering | |
|---|---|---|---|---|---|---|---|---|
| | verbal test (1) | math test (2) | verbal test (3) | math test (4) | verbal test (5) | math test (6) | verbal test (7) | math test (8) |
| PM2.5 level | -0.132** | -0.139*** | -0.161** | -0.135** | -0.417** | -0.267** | -0.137** | -0.144*** |
| | (0.060) | (0.052) | (0.064) | (0.056) | (0.170) | (0.118) | (0.060) | (0.051) |
| Observations | 9,038 | 9,038 | 9,038 | 9,038 | 9,038 | 9,038 | 9,038 | 9,038 |
| KP first-stage F-statistic | 719.7 | 719.7 | 550.2 | 550.2 | 185 | 185 | 726.2 | 726.2 |
| Demographic controls | N | N | Y | Y | Y | Y | Y | Y |
| Birth city FE | Y | Y | Y | Y | N | N | Y | Y |
| Birth year and month FE | Y | Y | N | N | N | N | Y | Y |
| Birth year-by-month FE | N | N | Y | Y | Y | Y | N | N |
| Birth city-by-year FE | N | N | N | N | Y | Y | N | N |
| Birth city-by-month FE | N | N | N | N | Y | Y | N | N |
| Clustering | one-way | one-way | one-way | one-way | one-way | one-way | two-way | two-way |

*Notes:* All the regressions include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Demographic controls include gender, maternal age, and mother's education years. Robust standard errors, clustered at the birth city level in columns (1)-(6) and two-way clustered at the birth city and birth year-season levels in columns (7)-(8), are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table A4: Mechanism test: heterogeneous effect on years of education based on the number of siblings and their gender composition (2SLS)

| VARIABLE | years of education | | | | |
|---|---|---|---|---|---|
| | **full sample** (1) | **only child** (2) | **having siblings** (3) | **having brothers** (4) | **having only sisters** (5) |
| | | | Panel A. *Female* | | |
| PM2.5 level | -0.157** | -0.311 | -0.142* | -0.227** | -0.016 |
| | (0.073) | (0.195) | (0.075) | (0.090) | (0.167) |
| Observations | 2,244 | 354 | 1,890 | 1,442 | 448 |
| KP first-stage F-statistic | 472.1 | 127.1 | 543.6 | 484.2 | 175 |
| | | | Panel B. *Male* | | |
| PM2.5 level | 0.054 | -0.026 | 0.047 | 0.109 | 0.006 |
| | (0.070) | (0.130) | (0.086) | (0.093) | (0.166) |
| Observations | 2,085 | 543 | 1,542 | 877 | 665 |
| KP first-stage F-statistic | 864.7 | 458.7 | 764.1 | 406.3 | 1216 |

*Notes:* The sample only includes individuals with completed education levels. All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table A5: Mechanism test: heterogeneous effect on age-appropriate grade completion based on the number of siblings and their gender composition (2SLS)

| VARIABLE | age-appropriate grade completion | | | | |
|---|---|---|---|---|---|
| | **full sample** (1) | **only child** (2) | **having siblings** (3) | **having brothers** (4) | **having only sisters** (5) |
| | | | Panel A. *Female* | | |
| PM2.5 level | -0.009** | -0.001 | -0.015*** | -0.021*** | -0.009 |
| | (0.005) | (0.004) | (0.006) | (0.007) | (0.012) |
| Observations | 4,575 | 1,034 | 3,541 | 2,654 | 887 |
| KP first-stage F-statistic | 553.8 | 418.4 | 643.5 | 504.4 | 456.1 |
| | | | Panel B. *Male* | | |
| PM2.5 level | -0.002 | 0.001 | -0.004 | 0.001 | -0.008 |
| | (0.004) | (0.006) | (0.006) | (0.007) | (0.008) |
| Observations | 4,463 | 1,446 | 3,017 | 1,589 | 1,428 |
| KP first-stage F-statistic | 724.6 | 593.5 | 456.3 | 306.7 | 529.4 |

*Notes:* All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table A6: Mechanism test: Heterogeneous effect on time spend helping child with homework based on the number of siblings and their gender composition (2SLS)

| VARIABLE | log form of time spend helping child with homework (hours per week) | | | | |
|---|---|---|---|---|---|
| | **full sample** | **only child** | **having siblings** | **having brothers** | **having only sisters** |
| | (1) | (2) | (3) | (4) | (5) |
| | | | Panel A. *Female* | | |
| PM2.5 level | -0.026** | -0.032 | -0.046** | -0.043* | -0.062 |
| | (0.012) | (0.021) | (0.020) | (0.022) | (0.058) |
| Observations | 1,529 | 431 | 1,098 | 813 | 285 |
| KP first-stage F-statistic | 364.2 | 298 | 525.7 | 439.4 | 155.7 |
| | | | Panel B. *Male* | | |
| PM2.5 level | 0.006 | -0.016 | 0.021 | -0.008 | 0.064* |
| | (0.016) | (0.026) | (0.023) | (0.031) | (0.034) |
| Observations | 1,548 | 582 | 966 | 469 | 497 |
| KP first-stage F-statistic | 266 | 197.2 | 164.1 | 74.95 | 149.1 |

*Notes:* Due to data availability, the sample only includes children younger than 16. All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.

Table A7: Mechanism test: effects of PM2.5 on health outcomes (2SLS)

| VARIABLES | birth health | | | | child health | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | birthweight (log form) | | low birth weight | | thinness (BAZ¡-2) | | stunting (HAZ¡-2) | | number of times being sick last month | |
| | female (1) | male (2) | female (3) | male (4) | female (5) | male (6) | female (7) | male (8) | female (9) | male (10) |
| PM2.5 level | 0.000 | 0.001 | 0.001 | -0.002 | -0.000 | -0.001 | -0.000 | 0.002 | 0.001 | 0.005 |
| | (0.001) | (0.001) | (0.002) | (0.001) | (0.002) | (0.002) | (0.003) | (0.003) | (0.006) | (0.006) |
| Observations | 3,252 | 3,713 | 3,252 | 3,713 | 3,375 | 3,826 | 3,460 | 3,905 | 3,856 | 4,356 |
| KP first-stage F-statistic | 1950 | 982.4 | 1950 | 982.4 | 1785 | 942 | 1769 | 857.2 | 1914 | 782.4 |
| Mean of Dep. Var. | 6.256 | 6.538 | 0.0698 | 0.0552 | 0.150 | 0.132 | 0.309 | 0.329 | 0.486 | 0.538 |

*Notes:* Due to data availability, the sample only includes children younger than 16. BAZ represents BMI-for-age z-scores, and HAZ denotes height-for-age z-scores. The z-scores are calculated based on the WHO Child Growth Standards. All the regressions include demographic controls, weather controls, birth city fixed effects, and birth year and month fixed effects. Demographic controls include gender, maternal age, and mother's education years. Weather controls include the number of days falling in each temperature bin (<-4 °C, -4-0 °C, 0-4 °C, 4-8 °C, 8-12 °C, 12-16 °C [reference group], 16-20 °C, 20-24 °C, 24-28 °C, >28 °C), mean precipitation, mean wind speed, mean sunshine duration, and mean humidity with their square terms during the gestation period. Robust standard errors, clustered at the birth city level, are presented in parenthesis. * 10% significance level; ** 5% significance level; *** 1% significance level.