Effect of Air Pollution on Cognitive Performance in India

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Abstract

This paper provides a causal estimate of the contemporaneous impact of outdoor air pollution on cognitive and academic performance of children aged 8-11 years in India by combining satellite data on particulate matter (PM2.5) with the two rounds of Indian Human Development Survey. Our identification strategy relies on the use of thermal inversions as an instrument that generates exogenous variation in the pollution levels. Results show that exposure to average PM2.5 concentrations in the past 12 months prior to the month of test taken by the children has a significant detrimental impact on their cognitive ability in India. Specifically, a 1 $\mu g/m^3$ increase in average PM2.5 concentrations in the past 12 months decreases the math performance by 10-16 percentage points and the reading performance by 7-9 percentage points. We also find that there is a significant fall in the combined age-standardised cognitive score. The results imply that the cost of air pollution in India is much higher than estimated, and a narrow focus on health-related outcomes understate the magnitude of negative impact of pollution, as mental acuity is essential for higher productivity of children.

Keywords: Air pollution, Cognitive performance, Educational outcomes, India, Thermal inversions.

JEL codes: O12 O13 I15 I24 I25 Q53 Q56

I. Introduction

Air pollution is contamination of the environment caused by a build-up of any chemical, physical or biological agent that brings about a change in the natural characteristics of the atmosphere. [1]

Pollutants of major public health concern include a combination of sulphur dioxide (SO2), nitrogen dioxide (NO2), carbon monoxide (CO), fine particulate matter or PM2.5, PM10 and ozone. The most dangerous of these pollutants are PM2.5 and NO2. According to the World Air Quality Report, 2018, 64% of all cities worldwide exceeded the annual exposure guideline for fine particulate matter of 2.5 micrometres or less in diameter (PM2.5), given by the World Health Organisation (WHO).

The problem of air pollution has reached an alarming stage in developing countries like India; on an average, the majority of the cities in India exceeded the safe threshold of PM2.5 emissions given by the WHO by almost 500%.[2] The major contributors to air pollution are household emissions, coal combustion, crop residue burning, industrial emissions and vehicular pollution.

It is well established in the literature that pollution negatively affects human health (The Lancet 2012, Cohen et al. 2017). PM2.5 is an extremely harmful air pollutant due to the small size of the particles that can easily penetrate into the lungs and blood, and affect the supply of oxygen to the brain which can impair cognitive function (Pope and Dockery 2006, Weuve 2012). Since pollution impedes proper brain functioning, it may cause fatigue and patchy memory (Kampa and Castanas 2008). This is especially harmful for children and adolescents, not only because

1 World Health Organisation (WHO).

2 2019 World Air Quality Report (IQAir, 2019).

it has the potential of adversely impacting academic performance and subsequent economic productivity, but also because of potential lifelong issues around ill-health and quality of life. Proper brain functioning is a critical determinant of academic achievement and subsequent efficient performance in most occupations, and, therefore, anything that causes impairment in early childhood hurts the chances of leading a fulfilling life. Considering the already significant levels of poverty, malnutrition and morbidities in a majority of children in India[3], cognitive impairment - resulting from exposure to pollution - can make the situation worse, especially for the poorest families in the country. Without taking into account these long-term impacts, it can safely be said that the estimated cost of pollution in India - which is already very high - is actually an underestimation.

The objective of this paper is to examine the contemporaneous effect of air pollution on the cognitive skills of children in India. The study links a nationally-representative data, Indian Human Development Survey (IHDS), with the satellite data on air pollution for the two survey round periods, 2004-05 and 2011-12, to examine how exposure to pollution can negatively affect the academic performance and cognitive ability of children. We match the IHDS dataset with the air pollution dataset at district level and estimate the impact on academic performance by controlling for other possible confounding effects of individual as well as household characteristics in addition to pollution levels, and add fixed effects to control for selected variables. We use two estimation techniques, namely, Ordinary Least Square (OLS) and Instrumental Variable (IV) approach to get a causal estimate of the impact of air pollution.

The rest of the paper is organised as follows: Section 2 provides a brief background on the problem of air pollution in India, Section 3 reviews previous studies on the impact of air pollution on cognition, Section 4 presents the datasets used and summary statistics of the main

3 "Global Multidimensional Poverty Index 2019: Illuminating Inequalities | OPHI", 2021.

variables, Section 5 explains the empirical methodology and the identification strategy, and Section 6 presents the empirical results. Finally, Section 7 discusses the implications of the results.

II. Air Pollution in India

Every year, the Indo-Gangetic plain records hazardous levels of air pollution with the onset of winters. During the winter season, the subtropical jet streams[4] shift to the south of the Himalayas and blow over North India from west to east. These jet streams develop anticyclones or high-pressure conditions in the upper troposphere.[5] In these high-pressure conditions the air sinks, thereby compressing the lower layers of air. As a consequence, the lower layers of air become warm due to compression.[6] This leads to the presence of warm air above cold air and this is how thermal inversion is created in the lower part of the troposphere. The temperature, after decreasing to a very low level of altitude in the troposphere, reverses and starts rising with altitude because of temperature inversion.[7] At the earth's surface, when fossil fuel or crop residue is burnt, the air parcels above it become hot, polluted and lighter than the surrounding air. These air parcels become unstable and start ascending till their temperature matches with the temperature of the surrounding air. At that point it stabilises and the pollution disperses there. However, the impact of temperature inversion does not allow the warm and unstable air

4 It is a belt of winds moving at a very high speed in the upper-most layer of the troposphere, lying above regions of subtropical high pressure.

5 Troposphere is the lowest layer of the atmosphere and stretches from the ground surface to an altitude of about 10–15 km.

6 Adiabatic lapse rate is the rate of temperature change that occurs within a rising or descending air mass. It is a process in which there is no exchange of heat with the atmosphere. Therefore, compression of air mass results in warming, whereas expansion results in cooling.

7 The normal lapse rate of temperature is the rate at which temperature of air declines with the altitude at the rate of 6.5°C per kilometre in the troposphere.

parcel to ascend, because its temperature matches with the temperature of the surrounding air, which happens close to the earth's surface. As a result, the air mass stabilises and pollution gets dispersed at a lower altitude. As long as temperature inversion exists, the pollution keeps on accumulating in the lower part of the troposphere, near the earth's surface, and thus, it affects human life adversely.

In a recent study[8] it was found that two groundwater conservation measures[9], enacted in Haryana and Punjab, inadvertently exacerbated the problem of air pollution in the region. In order to conserve groundwater (which is used by farmers extensively for irrigating crops in the months devoid of monsoon rains) the governments of Punjab and Haryana, respectively, came up with a law that delayed groundwater use by farmers until later in the season. The legislations passed by these state governments prohibited transplanting of rice into paddies until after June. The expectation of the lawmakers was that it would protect groundwater from over-exploitation, as the farmers would be more inclined to use rainwater to irrigate their crops rather than groundwater, since it would be readily available from July onwards (arrival of monsoons).

The implementation of these laws resulted in delaying the harvest and shifting it to late October and early November. This led to a narrower window to harvest rice, as the farmers were, and still are, under pressure to prepare their lands for the next crop of wheat. This in turn caused an increase in crop residue resulting in stubble burning in the first three weeks of November. Because of the anticyclonic (high pressure) conditions and temperature inversion, the pollution created over the ground by stubble burning does not lift up into the atmosphere for dispersion.

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8 "Trade-off Between Groundwater Conservation and Air Pollution From Agricultural Fires in Northwest India", done as a collaboration between researchers from Cornell and the International Maize and Wheat Improvement Centre (CIMMYT).

9 The Punjab Preservation of Subsoil Water Act and the Haryana Preservation of Subsoil Water Act (the groundwater acts), 2009.

Instead, it accumulates in the lower atmosphere, leading to an increased concentration of pollutants.

A recent study done by the Centre for Science and Environment (CSE)[10] found that in 2020, the southern states in India also witnessed a surge in air pollution. Most importantly, while many larger cities recorded a slight fall in annual trends in PM2.5, smaller towns and cities witnessed an increase in pollution levels, signifying a regional build-up of pollution. Clearly, the natural advantage of warmer temperatures in winter and sea breeze blowing over the southern states is not sufficient to fully insulate them from pollution. Thus, the problem of air pollution is neither restricted to the Indo-Gangetic plain nor to the winter season. Out of 30 most polluted cities in the world, 22 cities belong to India.[11] The alarming rate of increase in pollution in the country makes it imperative to study its various far-reaching effects including its impact on human capital formation.

III. Literature Review

Most of the studies on the impact of pollution are based on developed nations. People living in low-income and middle-income countries are more vulnerable to the burden of outdoor air pollution, with 91% (of the 4.2 million premature deaths) occurring in low and middle-income countries. The additional risk in these countries comes from the pollutants due to burning of polluting fuels on open fires or traditional stoves for cooking, heating and other household purposes.

10 Roychowdhury and Somvanshi (2021). Decoding winter air pollution in cities of Southern India. 112020 World Air Quality Report (IQAir 2020).

High levels of air pollution can negatively affect children both physically and mentally (Gauderman et al. 2002; Evans 2003). A large body of literature has established a negative association between air pollution and its impact on human health, in terms of infant mortality, child growth indicators, and child health. Tanaka (2015) examined the effect of stringent air pollution regulations and found that infant mortality rate (IMR) decreased by 20% in the cities of China that had introduced these regulations. Currie and Neidell (2005) found that a one unit reduction in both carbon monoxide and PM10 in the air saves 1000 infants in California. In India, Greenstone and Hanna (2014) observed that there is a negative impact of water and air pollution on IMR. Do et al. (2018) have shown how environmental regulations to combat industrial pollution in the Ganga River resulted in a fall in water pollution levels, which in turn reduced infant deaths in the region.

Exposure to air pollution can affect a foetus's health as it impairs the placental growth in the mother's womb by affecting the oxygen supply and flow of nutrients to the foetus (Almond and Currie 2011). Thus, even if a child survives infancy, the negative impact of exposure to air pollution shows up in adverse birth outcomes such as low birth weight and preterm birth. In a study done in India, Singh et al. (2019) found that exposure to air pollution (PM2.5) during the first trimester increases the likelihood of children, aged below five years, being stunted and underweight. An increase of 31.87 ug/m3 in PM2.5 is associated with a 6.7% decline in Height-for-age and a 7.8% decline in Weight-for-age and the negative effect of PM2.5 is greater for poorer households, with northern states in India being more vulnerable due to the presence of higher pollution levels. Similarly, Spears et al. (2019) show that exposure to PM2.5 in the last trimester of pregnancy and in the initial months after birth are associated with child height deficits. Stunting in early childhood can cause irreversible damage as it is correlated to many long-term health and educational outcomes, for example, height deficits in adults, decline in cognitive functions, lower educational attainment, reduced productivity, and a decline in birth weight of the offspring (Mendez and Adair 1999; Spears 2012). In short, pollution exposure at any stage in life has long term negative consequences throughout life.

There are limited studies which attempt to study the negative impact of air pollution on human capital formation. Literature from epidemiology shows that air pollution can cause inflammation in the brain by depressing the neurons and white matter cells (Costa et al. 2014). Perera et al. (2009) showed that in the city of New York, prenatal exposure to polycyclic aromatic hydrocarbons causes a decline in children's IQ at the age of 5. Ioar Rivas et al. (2019) show that in Barcelona, exposure to PM2.5, in-utero and during the initial years of life, is negatively associated with cognitive abilities of children (7-10 years), such as working memory (association being present only for males) and executive attention (present for both males and females). Bharadwaj et al. (2017) found a negative effect of exposure of foetuses to carbon monoxide on numeracy and literacy skills of children in 4th grade in Chile. Zhang et al. (2018) measured the impact of air pollution on cognitive development in China, by using a longitudinal dataset. They found that air pollution is negatively associated with cognitive performance and this negative association becomes stronger when the window of exposure increases.

If air pollution impairs cognitive ability, then, the negative consequences of pollution may extend to everyday activities that involve mental dexterity. Insofar as air pollution may lead to reduced cognitive performance, the consequences of pollution may be relevant for a variety of everyday activities that require mental acuity. Ebenstein et al. (2016) show that transitory PM2.5 exposure is associated with a significant deterioration in the performance of Israeli students in the matriculation exam. Furthermore, exposure to PM2.5 during exams is also negatively associated with postsecondary educational attainment and earnings of the same students. Molina (2021) found that in utero exposure to air pollution lowers cognitive ability in adulthood in Mexico by using thermal inversions as an instrument for pollution. Using a similar methodology, Balakrishnan and Tsaneva (2021) have shown that higher annual PM2.5 levels lead to lower math and reading performance of children in India. Clearly, this indicates that the losses estimated from increasing levels of pollution may be underestimated if restricted to merely to standard health impacts.

We attempt to extend this literature by examining the link between contemporaneous exposure to pollution and the cognitive ability of children in India.

IV. Research Questions and Data

This study contributes to the literature in three ways. First, it adds to the current literature about the detrimental impact of air pollution on educational outcomes. By using an extensive household level panel survey data, we attempt a comprehensive analysis, controlling for heterogeneity at the individual level. Second, this is among one of the first studies examining the relationship between air pollution and cognitive skills of children in India. The only other similar work is by Balakrishnan and Tsaneva (2021), who measure this association with a different dataset.[11] We add to the findings by extending our study to urban areas as well, and controlling for a richer set of household as well child characteristics along with month of the test taken by the child. Additionally, we take into account the fact that some children are born with an innate ability to perform better in a particular subject like mathematics and language and estimate the results for a combined score of math and reading skills for a child. Third, we use the findings of this paper to re-emphasize the importance of controlling air pollution in India from the perspective of human capital accumulation.

11 ASER India Data.

This study combines several data sources to examine the contemporaneous effect of exposure to air pollution on the cognitive skills of children. This section describes all the datasets used in the study.

Demographic Data

Several data sources have been used in the present study. The first is a panel dataset from India Human Development Survey (IHDS), conducted jointly by the National Council of Applied Economic Research and the University of Maryland. The two rounds, 2004-05 and 2011-12 contain information on education, health, economic status, and results of cognitive tests. The first round of this dataset contains extensive information on 215,754 individuals from 41,554 households across India (Desai and Banerjee 2008) and in the subsequent round, 83% of these households were reinterviewed, that is, 204,569 individuals from 42,152 households across India (Desai and Vanneman 2015). The survey collected data by drawing samples using stratified random sampling.

The cognitive tests are categorical variables and were administered to children in the age-group of 8-11 years (present in the same household) in both the rounds. The reading test for assessing the reading skills divided children into five categories: (i) cannot read, (ii) can read letters, (iii) can read words, (iv) can read a paragraph, and (v) can read a story. The arithmetic skills were tested through the math test which recorded scores across four categories: (i) cannot do math, (ii) understands numbers, (iii) can do subtraction, and (iv) can do division. For the purpose of this study, we put together these two indicators of cognitive skills to create a combined score of cognition.

IHDS also contains demographic information on the child and the child's household characteristics, such as age, gender, caste, religion, hours spent in doing home-work, type of school attended, parents' education, income, and other household-level characteristics. IHDS has the advantage of being an all-India data-set as it includes all the states and union territories of India (except for Andaman and Nicobar Islands, and Lakshadweep) and, therefore, is more representative.

In this study, we used the data on cognitive tests from both the rounds of IHDS to estimate the impact of cumulative annual exposure to PM2.5. The cognitive tests were administered to the children at home and, therefore, includes children who are enrolled in school as well as those not enrolled in any school, which reduces the risk of selection bias pertaining to school enrolment or accessibility to schools. Furthermore, IHDS offers the advantage of a diverse sample as it includes both rural and urban areas.

Air Pollution Data

The ground-based pollution data maintained by the Central Pollution Control Board (CPCB) has data on PM2.5 beginning from only 2009 and suffers from limited reach in terms of the number of monitoring stations which tend to be concentrated in urban areas or capital cities such as Delhi. Over the years, the number of monitoring stations have also increased in some cities. In order to eliminate the bias from the measurement error of pollution, it is important to have a long-term database at a high spatial resolution. Therefore, this study used the satellite data for PM2.5. The data on PM2.5 was derived from the MODIS instrument using the Multiple Angle Implication of Atmospheric Correction (MAIAC) algorithm which is used for aerosol retrieval. Scaling factors from MERRA-2 reanalysis data were used to readjust the data against measurements done at ground-level monitoring stations managed by the Central Pollution Control Board (CPCB) in India. So, the extracted PM2.5 data was available at monthly frequency at a high resolution of 1 km × 1 km and spans two decades (2000–2019) for India (Dey et al., 2020). Since there is no comprehensive data on other harmful air pollutants such as NO2, SO2 and CO, the data on PM2.5 offers an advantage as it is correlated with these other air pollutants.

We merged the IHDS data with the pollution data at district level by matching the year and month in which the cognitive tests were taken with the pollution data. The final data was a sample of cognitive test data of children who were born in the same household for the years 2004-05 and 2011-12.

Thermal Inversion Data

Temperature inversion is a condition in which the temperature of the atmosphere increases with altitude in contrast to the normal decrease with altitude. It is well established in the literature that events of temperature inversions are positively associated with levels of pollution (Bailey et. al 2011; Trinh et. al 2019; Chen, Oliva & Zhang 2022). Therefore, we used the night-time inversions to instrument for air pollution because are generated by idiosyncratic atmospheric conditions, which is necessary for a causal estimation.

To capture the events of temperature inversion in India, we used the reanalysis data, from NCEP/NCAR, that records air temperatures at two pressure levels, that is, 1000 hPa and 925 hPa, at 2.5x2.5-degree grid (roughly 250kms by 250kms). The ground level temperature was measured by the 1000 hPa layer and the temperature conditions at 600m above sea level was measured by the 925 hPa layer (Jans et al. 2018). In the event of temperature inversion, the normal lapse rate of temperature reverses and the difference between these two pressure layers becomes positive.

We measured thermal inversion by taking the difference in temperature between the two atmospheric pressure layers, namely, 925 hPa and 1000 hPa, for each day recorded at 12:00am.

We then calculated the number of days per month with a night-time inversion and measured the average number of inversions in the past 12 months at the district level.

Weather Data

Weather controls such as wind speed, precipitation and temperature are important for a causal estimation as they can influence the occurrence of a thermal inversion as well as the pollution levels. It is well-established in the literature that rainfall and temperature shocks affect the developmental indicators of a child. Therefore, inclusion of weather variables as control variables is necessary to ensure that the inversion episodes are affecting the outcomes through the channel of pollution only and not through the weather variables.

The data on wind speed is taken from ERA5, the fifth-generation European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis dataset which records the wind speed at a height of 10m above the ground with a resolution of 0.5° × 0.5° grid. We used data of u (zonal wind) and v (meridional wind) to calculate the wind speed by using the following formula (Chowdhury et al. 2017, Singh et al. 2019):

$$WindSpeed = \sqrt{(u)^2 + (v)^2}$$

Precipitation and temperature datasets were sourced from the University of Delaware which are available at a resolution of 0.5° × 0.5° for the time period 1900-2017.

We extracted the data on PM2.5, temperature inversion and the weather variables at district-level and merged them with the IHDS data at district-level by matching the year and month of cognitive tests taken by the child.

Combined Score of Cognition

Research done in the field of psychology has been established that math ability in children is associated with their inborn number-sense.[12] Therefore, to get a holistic assessment of cognitive skills, we used a new method to calculate the combined score of cognition by taking into account the performance of a child in both math as well as reading tests. The math test records scores across four categories and gives them the following scores: (i) cannot do math=0, (ii) understands numbers=1, (iii) can do subtraction=2, and (iv) can do division=3. Similarly, the reading test divides children into five categories and gives them the following scores: (i) cannot read=0, (ii) can read letters=1, (iii) can read words=2, (iv) can read a paragraph=3, and (v) can read a story=4. A higher number implies a higher level of skill and is inclusive of lower levels of skills. For example, if a child is able to subtract one number from the other number, it implies that the child understands numbers as well. To calculate the maximum score that a child can get, we added the number of categories given in both the tests, that is, seven (=3+4). We first defined the numerator as the sum of the numbers given in the math and reading test, and then calculated the combined score by taking the ratio of this sum and total number of categories in both the tests. Finally, we standardised this ratio by age of the child as the cognitive abilities vary by age. Table 1 shows the calculation of the combined score of cognition.

Table 1: Calculation of Combined Cognitive Score

12 Ability to do maths in preschool children is closely associated with their inborn and primitive "number sense," called an "Approximate Number System". Johns Hopkins University. (2011, August 8). You can count on this: Math ability is inborn, new research suggests. ScienceDaily. Retrieved February 11, 2022 from www.sciencedaily.com/releases/2011/08/110808152428.htm

Math Test	**Math Score**	**Reading Test**	**Reading Score**
Cannot do math	0	Cannot read	0
Numbers	1	Letter	1
Subtraction	1+1 = 2	Word	1+1 = 2
Division	1+1+1 = 3	Paragraph	1+1+1 = 3
		Story	1+1+1+1 = 4
Maximum Score	3		4

Table 2 shows the summary statistics for our estimation sample. 53 percent of children in our sample are males. On average, the highest female adult education in a household is 4 years of education. Almost four-fifth of the sample comprises rural households. In the total sample, 14 percent of households reported to be Muslims and 31% of the sample belong to marginalised sections of the society that includes scheduled caste and scheduled tribes. The mean household size was found to be 6, with mean asset index of 12. Twenty nine percent of the households in the sample used Liquified Petroleum Gas (LPG). The average level of PM2.5 in India is 64.6 $\mu g/m^3$. On an average, there are approximately 81 episodes of night-time inversions in a year across India.

Table 2: Summary Statistics

Variable	Mean
Rural	0.789
Highest Female Adult Education	3.904
Assets	11.913
LPG	0.285
Household Size	6.198
Sex	0.533
Muslim	0.139
SC/ST	0.311
Private School	0.293
Takes Private Tuition	0.214
PM2.5	64.618
Inversion	81.412
Relative Humidity	59.714
Wind Speed	2.353
Temperature	25.36
Precipitation	99.592

IHDS sampling weights are used for the demographic variables.

V. Empirical Strategy

We investigated the impact of exposure to air pollution on the cognitive performance of children, measured by the cognitive tests. We started by first estimating the following OLS specification:

$$Yilym = \beta 0 + \beta 1PM2.5lym + \beta 2Xilym + Wlym + \delta l + \rho st + \gamma m + \epsilon ilym \qquad (1)$$

where Y_{ilym} is the main outcome of interest (cognitive test) for a child i residing in location l in survey year y in month m. $PM2.5_{lym}$ is the mean level PM2.5 concentrations in the past 12 months. Individual and household level controls, X_{ilym}, include an indicator for sex, asset index, household size, religion, caste, highest female adult education, type of school (private or government) and whether the child takes private tuition or not. The asset index included 30 housing goods and amenities to reflect the long-term economic status of the household. To account for indoor air pollution, we included an indicator for usage of Liquified Petroleum Gas (LPG) as fuel in the household.

To account for time-invariant district-level and primary sampling unit (Primary Sample Unit or PSU/villages/urban blocks)-level heterogeneity, we show results with district fixed effects and PSU fixed effects in our specification, δ_l. The inclusion of the district fixed effects means that the variation that remains is both spatial as well as temporal within a year for a district and inclusion of PSU fixed effects means that the remaining variation comes from temporal variation for a PSU. We also removed any omitted variables that are related to a state in any particular year, for instance, any change in education policy, as well as any seasonality effect specific to a month by including a state-year specific fixed effect, ρ_{st} and a month fixed effect, γ_m. We included a vector of weather controls, W_{lym}, as they are time-varying factors that may be contemporaneous with pollution. The standard errors were clustered at the household level to allow for correlation of the error term within a household. ϵ denotes the error term.

However, there are a few endogeneity issues in specification (1). The differences in pollution levels are not strictly random and may vary systematically with economic activity. For example, areas characterised by higher economic activity may be associated with higher levels of air pollution. Furthermore, households can observe and change their behavioural choices in response to different pollution levels. For example, richer households are better-equipped to choose to live in areas with low levels of pollution. To address these endogeneity problems, we used episodes of thermal inversions to instrument air pollution to capture causal estimates of the impact of PM2.5 on the cognitive performance of children. In specification (1), we measure thermal-inversions as the average number of daily night-time inversions occurring in district d in the past 12 months from the month of test taken by the child and use this as an instrument for PM2.5 levels. Thermal inversions can be hypothesised to be correlated with PM2.5 levels but not related to the educational outcomes of the children through channels other than the concentrations of PM2.5. We also included linear as well as non-linear forms of the weather variables such as temperature, wind speed, precipitation and relative humidity because they exert influence on the occurrence of a thermal inversion and are also likely to affect the magnitude of pollution levels at any location.

VI. Results

Ordinary Least Square (OLS) Estimates

Table 3 shows the empirical results of model (1) with math test as the dependent variable. The dependent variable in all the columns is a dummy variable that takes value 1 if the child can read numbers and is able to do mathematical operations such as subtraction and division, and 0 otherwise. Holding other factors constant, there is no significant effect of pollution on the math skills in any of the columns.

Table 3: OLS Estimates: Impact of Pollution on Math Performance

	Math Test	**Math Test**
Mean PM2.5	-0.003	-0.003
Highest Female Adult Education	0.006***	0.005***
Assets	0.008***	0.008***
LPG	-0.001	0.004
Household Size	-0.004***	-0.004***
Sex (Female = 0)	0.032***	0.032***
Age	0.040***	0.040***
Muslim	-0.049***	-0.025*
SC/ST	-0.040***	-0.045***
Private School	0.057***	0.064***
Takes Private Tuition	0.040***	0.035***
Observations	18375	18238
Weather Controls	Yes	Yes
District FE	Yes	No
PSU FE	No	Yes
Month FE	Yes	Yes
Survey FE	Yes	Yes
State-Specific Time Trends	Yes	Yes

Dependent variable is a binary variable (0: Cannot do math, 1: Otherwise).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Similarly, in Table 4, the dependent variable in all the columns is a dummy variable that takes value 1 if the child can read letters/words/paragraphs/stories, and 0 otherwise. Holding other factors constant, there is no significant impact of PM2.5 on the reading skills of the children. The usage of LPG has no significant impact on either the math or the reading skills.

Table 4: OLS Estimates: Impact of Pollution on Reading Performance

	Reading Test	**Reading Test**
Mean PM2.5	-0.001	-0.001
Highest Female Adult Education	0.004***	0.004***
Assets	0.007***	0.006***
LPG	-0.010	-0.010
Household Size	-0.003***	-0.003***
Sex (Female = 0)	0.010**	0.011**
Age	0.029***	0.030***
Muslim	-0.045***	-0.030**
SC/ST	-0.025***	-0.024***
Private School	0.047***	0.051***
Takes Private Tuition	0.031***	0.029***
Observations	18375	18238
Weather Controls	Yes	Yes
District FE	Yes	No
PSU FE	No	Yes
Month FE	Yes	Yes

Survey FE	Yes	Yes
State-Specific Time Trends	Yes	Yes

Dependent variable is a binary variable (0: Cannot read, 1: Otherwise).

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 5: OLS Estimates: Impact of Pollution on Combined Age-Standardized Cognitive Score

	Cognitive Test	**Cognitive Test**
Mean PM2.5	-0.008*	-0.009
Highest Female Adult Education	0.029***	0.027***
Assets	0.036***	0.033***
LPG	0.045**	0.056**
Household Size	-0.022***	-0.019***
Sex (Female = 0)	0.059***	0.051***
Muslim	-0.231***	-0.137***
SC/ST	-0.143***	-0.139***
Private School	0.234***	0.259***
Takes Private Tuition	0.175***	0.173***
Observations	18375	18238
Weather Controls	Yes	Yes
District FE	Yes	No
PSU FE	No	Yes
Month FE	Yes	Yes
Survey FE	Yes	Yes

State-Specific Time Trends	Yes	Yes

Dependent variable: Standardized Combined Cognitive Score.

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 5 shows the ordinary least square estimates in which the dependent variable is the age-standardised combined cognitive score of both math and reading tests. In column 3, holding other factors constant, a unit increase in the concentration of PM2.5 is associated with a fall in the age-standardised score of 0.008 SD[13] units at significance level of 10%. Additionally, the coefficient on the variable LPG becomes significant at 5% level under all the columns. Holding other factors constant, use of LPG is associated with a decline in the age-standardised cognitive score of 0.045 SD units under column 3.

In Table 3, Table 4 and Table 5, boys significantly perform better than girls in both math and reading tests. The socio-economic variables are highly significant as the children belonging to a Muslim household or scheduled caste/tribe category record a lower performance in both the cognitive tests. Higher levels of assets indicate higher economic status of the household and there is a positive association between the asset index and performance of children in both the tests. For all the children, their skills of math and reading increase with age. An increase in the household size is associated with a lower performance as it signifies more competition for limited economic resources of the household and less attention to the child. Children attending a private school and using private tuition, to supplement their education, perform better in math and reading tests. As the highest number of years of education of female members in the

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household increases, the performance of the children belonging to such households is better in both the tests, ceteris paribus.

VII. 2SLS

We used the night-time inversions as an instrument for air pollution because they are strongly associated with higher levels of air pollution. Most importantly, thermal inversions are generated by idiosyncratic atmospheric conditions, which is necessary for a causal estimation, as people are less likely to observe them and change their behaviour in response to them (Molina, 2021).

To test whether the chosen IV meets exclusion restriction, we show some suggestive evidence in Table 9. We regressed various individual as well as household characteristics, included in the main specification, that affect the cognitive skills of a child on the chosen IV - thermal inversions. Insignificant regression results suggest that there is no systematic relationship between the IV and these individual and household characteristics. Columns 1 to 9 in Table 9 show that highest female adult education, assets, LPG, sex, Muslim SC/ST, private school, household size, and whether the child takes private tuition, which are control variables in our main specification, are not systematically related to the IV. The only exception is household size which is negatively correlated with our IV in column 8 but only at 10% significance.

Table 6: IV Estimates: Impact of Pollution on Math Test

	Math	**Math**
Panel A: Second Stage Results		
Mean PM2.5	-0.101***	-0.164***
Highest Female Adult Education	0.007***	0.006***
Assets	0.008***	0.006***
LPG	0.001	0.012
Household Size	-0.004***	-0.004***
Sex (Female = 0)	0.032***	0.031***
Age	0.040***	0.041***
Private School	0.062***	0.069***
Takes Private Tuition	0.046***	0.044***
Panel B: First-Stage Results & Test Statistics		
Thermal Inversion	0.2729***	0.2860***
Cragg-Donald Wald F statistic	87.53	78.00
Kleibergen-Paap Wald rk F statistic	42.15	25.90
Observations	18389	18253
Weather Controls	Yes	Yes
District FE	Yes	No
PSU FE	No	Yes
Month FE	Yes	Yes
Survey FE	Yes	Yes

State-Specific Time Trends	Yes	Yes

Dependent variable is a binary variable (0: Cannot do math, 1: Otherwise).

* p < 0.10, ** p < 0.05, *** p < 0.01

Table 6 shows the empirical results of 2SLS for the math test. Even after controlling for a complete set of fixed effects, state-specific time trends, weather controls and individual level controls, thermal inversions are positively and significantly (at 1% level) related to PM2.5 levels. The two statistics (Crag-Donald F statistics and Kleibergen-Paap F statistics) in this first-stage show that the instrumental variable is a strong one, as the values exceed conventional thresholds for strong instruments.

Air pollution has a significant negative impact on the childrens' performance on the math test. In column 1, a one unit increase in the average levels of PM2.5 lead to a decline in the math scores of 10.1 percentage points and in column 2 it causes a decline of 16.4 percentage points, at 1% significance. Compared with the ordinary least square results where pollution is regarded as an exogenous variable, the negative impact becomes larger and significant for the math performance.

Table 7: IV Estimates: Impact of Pollution on Reading Test

	Reading	**Reading**
Panel A: Second Stage Results		
Mean PM2.5	-0.074***	-0.093***
Highest Female Adult Education	0.005***	0.005***
Assets	0.006***	0.005***
LPG	-0.009	-0.005

Household Size	-0.003***	-0.003***
Sex (Female = 0)	0.010**	0.010**
Age	0.029***	0.030***
Private School	0.051***	0.054***
Takes Private Tuition	0.036***	0.034***
Panel B: First-Stage Results & Test Statistics		
Thermal Inversion	0.2729***	0.2860***
Cragg-Donald Wald F statistic	87.53	78.00
Kleibergen-Paap Wald rk F statistic	42.15	25.90
Observations	18389	18253
Weather Controls	Yes	Yes
District FE	Yes	No
PSU FE	No	Yes
Month FE	Yes	Yes
Survey FE	Yes	Yes
State-Specific Time Trends	Yes	Yes

Dependent variable is a binary variable (0: Cannot read, 1: Otherwise).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 shows the 2SLS results for the reading test. In column 1, a one unit increase in the average levels of PM2.5 causes a decline in the reading skills of 7 percentage points and in column 2, it leads to a fall of 9.3 percentage points, at 1% significance. Compared with the ordinary least squares results where pollution is regarded as an exogenous variable, the negative impact becomes larger and highly significant for the performance in the reading test. However, the magnitude of decline due to a rise in exposure to air pollution is larger for performance in the math test.

Table 8: IV Estimates: Impact of Pollution on Combined Age-Standardized Cognitive Score

	Cognitive Score	**Cognitive Score**
Panel A: Second Stage Results		
Mean PM2.5	-0.178**	-0.287***
Highest Female Adult Education	0.033***	0.030***
Assets	0.033***	0.031***
LPG	0.049**	0.071***
Household Size	-0.024***	-0.020***
Sex (Female = 0)	0.057***	0.048***
Private School	0.250***	0.273***
Takes Private Tuition	0.189***	0.188***
Panel B: First-Stage Results & Test Statistics		
Thermal Inversion	0.2729***	0.2860***
Cragg-Donald Wald F statistic	87.53	78.00
Kleibergen-Paap Wald rk F statistic	42.15	25.90
Observations	18389	18253
Weather Controls	Yes	Yes

District FE	Yes	No
PSU FE	No	Yes
Month FE	Yes	Yes
Survey FE	Yes	Yes
State-Specific Time Trends	Yes	Yes

Dependent variable: Standardized Cognitive Score.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The IV estimates for the combined age-standardised cognitive score are shown in Table 8. In column 1, at 5% level of significance, a one unit increase in the average annual levels of PM2.5 causes a decrease of 0.18 SD units and in column 2, it leads to a fall of 0.29 SD in the age-standardised cognitive score at 1% significance level. The magnitude of the negative impact of air pollution on the combined age-standardised cognitive score is larger than the results of ordinary least squares estimation.

Table 9: IV Validity

Identifying Instrument	Highest Female Adult Education	Assets	LPG	Sex	Muslim	SC/ST	Private School	Household Size	Private Tuition
Thermal Inversion	0.011	0.053	0.004	-0.005	0.000	0.016	0.006	-0.129*	0.000
Observations	18375	18375	18375	18375	18375	18381	18375	18375	18375
Thermal Inversion	-0.033	0.009	-0.009	-0.008	-0.000	0.019*	0.007	-0.097	-0.004
Observations	18238	18238	18238	18238	18238	18244	18238	18238	18238

First row includes district fixed and second row includes PSU fixed effects.

All regressions include weather controls, months fixed effects, survey fixed effects and state-specific time trends.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

VIII. Conclusion

The analysis shows that there is negative impact of exposure to air pollution on childrens' cognitive performance and educational outcomes. There is a limited focus on the impact of pollution on cognitive as well as other educational outcomes for children in India. The damage on a child's brain and health by air pollution can impose substantial health and economic costs, which is not usually mentioned in policies around pollution control in India. There may also be additional coping costs incurred at the household level to compensate for any deterioration in the health and cognitive abilities of children due to air pollution. The costs pertaining to cognitive damage can be very high if the damage persists over the lifetime of those affected. Thus, the estimated cost of pollution in India, which is already very high, is actually an underestimation. This has the potential to jeopardise the benefits of the projected demographic dividend and economic growth of the country. The results of this paper imply that a myopic assessment of the impact of pollution - focusing only on the health outcomes - would not be sufficient. There is an urgent need to look at health of individuals, especially children, in a holistic manner, taking into account all possible impacts, including that of pollution on cognitive ability, which has cumulative social and economic impact. This study serves as a reminder to the policy makers of the criticality of a pollution-free environment.

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