The Impact of River Water Quality on Children's Education: Evidence from 39 Districts in India

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Abstract

We investigate the effect of water quality on the educational outcomes of school-going children aged 8-11 in 39 districts in 5 states in the Ganges Basin of India. Using data from the Centre for Pollution Control Board of India and the Indian Human Development Survey (IHDS) 2011-12, we study the effect of water quality of river Ganges on the performance in three tests - maths, reading, and writing (N = 1147). Our evidence suggests that the effects of faecal coliform in water sources above safety levels on the reading and writing test scores are negative. The effect of Nitrate-N and Nitrite-N in the water appears to be weaker compared to faecal coliform's. The results establish that water pollution caused by excessive presence of faecal coliform is an important environmental factor in determining educational outcomes of children. High density of faecal coliform in the water could be lowering cognitive abilities of the pollution-affected children through the channel of water-borne diseases.

Keywords— River Pollution, Water Quality, Pollution and Education, Cognitive Abilities, Children's education.

JEL codes: I21, Q53, O15

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1 Introduction

The Ganges spans approximately 26% of India's territory and sustains nearly half of its population. (Chakraborti et al., 2018). Despite its importance, it is becoming one of the world's most polluted rivers due to growing populations, industrialisation, and urbanisation (Chaudhary and Walker, 2019). Urban areas near the Ganges saw a 30% population increase from 2001 to 2011, which likely worsened the pollution. (Census of India, 2011). Consequently, the pollution in the Ganges not only harms the environment but also poses significant health and economic consequences for the people living nearby. (Khan et al., 2016; Das and Birol, 2010; and others).

Many studies show that polluted water threatens public health and economic well-being. The Ganges, a key water source, is among the world's most polluted rivers (Chaudhary and Walker, 2019). Pollution can affect children's physical growth and cognitive development, as water filters may not remove all pollutants. This paper explores how pollution in the Ganges Basin affects the education of children aged 8-11 across 39 districts. Long-term exposure to pollution could impair cognitive abilities, potentially leading to lower educational achievements (Kyriklaki et al., 2016; Rodrigues et al., 2016; Dewey et al., 2023). We use data from the Central Pollution Control Board, (CPCB) (2012) and the 2011-12 wave of the Indian Human Development Survey (Desai and Vanneman, 2015) to analyse how organic and inorganic pollutants impact children's test scores. We focus on the effects of faecal coliform and Nitrate Nitrogen + Nitrite Nitrogen on children's reading, maths, and writing abilities. For brevity, we will refer to Nitrate Nitrogen + Nitrite Nitrogen as Nitrate-N + Nitrite-N henceforth.

Originating from the Gangotri glacier in Uttarakhand, India, the Ganges flows 2,525 kilometres across five states to the Bay of Bengal. It is essential for drinking, cooking, and irrigation. However, pollution from sewage, industrial waste, and agricultural runoff—exacerbated by population and industrial growth—poses a significant challenge. A report indicates 764 industries release 500 million litres of wastewater into the Ganges daily[1]. Heavy metals in the

[1] See *Annual Progress Report of CPCB ENVIS, Centre on Control of Pollution* (2016–2017) for more. Research, including a study in Varanasi, shows this pollution leads to water-borne diseases (Hamner et al., 2006).

water can cause kidney damage and cancer (Lellis et al., 2019). Furthermore, long-term consumption of water with heavy metal contents has been shown to impair cognitive function, according to several studies (Tyler and Allan, 2014; Tolins et al., 2014; Vahter et al., 2020; Mostafa et al., 2009; Siegal and Share, 1990). Nitrates and antibiotic-resistant bacteria in the water also pose health risks (Quist et al., 2018; Adimalla, 2020; Reddy and Dubey, 2019). This study examines the impact of fecal coliform and Nitrate-N + Nitrite-N on children's cognitive abilities and educational outcomes, establishing an association between polluted water in the Ganges and lower test scores.

Religious activities like ritual baths, idol immersion, and cremation add to the Ganges' pollution, increasing heavy-metal levels and the river's Biochemical Oxygen Demand (B.O.D), often exceeding the CPCB standards. During the *Maha Kumbh* festival, studies of the Ganges water show that such mass gatherings significantly raise B.O.D, total suspended solids, and ammonia nitrogen beyond safe limits for outdoor bathing. The water also shows high levels of faecal and total coliforms, leading to more water-borne diseases (Tyagi et al., 2013). Figure 1 illustrates the Indian states the Ganges flows through. Figures (2a) and (2b) depict the pollution intensity from faecal coliform and Nitrate-N + Nitrite-N in areas monitored by the CPCB, including the Ganges and its tributaries.

Several studies have shown that the water quality of the Ganges is unsuitable for drinking and bathing at many monitoring points (Mariya et al., 2019; Chauhan et al., 2009; Matta et al., 2017). This can pose a higher risk to human health (Chaudhri and Jha, 2012), and can potentially lead to lower cognitive abilities through the channel of health deterioration. When it comes to educational outcomes of children in the context of developing countries, researchers are more interested in socioeconomic and household conditions as determinants of children's education (Edmonds et al., 2009; Nambissan, 2009; Chaudhri and Jha, 2012). A growing literature provides evidence that exposure to pollutants, especially air pollutants, leads to lower educational outcomes in the US (Sanders, 2012; Roth, 2017; Rosofsky et al., 2014; Jasper et al., 2012; Evans et al., 2019; Mohai et al., 2011; Ebenstein et al., 2016). However, to the best of our knowledge, this is the first research examining specifically on the negative impact of poor water quality on educational outcomes in the context of a developing country like India.

Figure 1: Five States of India within the Ganges Basin

This paper investigates the understudied area of pollution's impact on education in developing countries like India. Water pollution leads to both immediate and long-term health issues, including negative effects on cognitive development from prolonged pollution exposure. Increased population density in polluted areas further exacerbates these effects, reducing children's cognitive abilities. Despite its importance, such research is limited, often overshadowed by urgent issues like child mortality. In developing countries, the emphasis on economic growth often results in less stringent pollution monitoring; stricter pollution laws potentially could increase production costs in the long run (Fuller et al., 2022). Moreover, while the discourse on environment and development priorities health and the reduction of child mortality, interest in educational outcomes often takes a backseat. Some studies that explored only the environmental and health outcomes were conducted after pollution control laws like the Ganga Action Plan were implemented (Dwivedi et al., 2018; Dutta et al., 2020). The lack of data for long-run health and cognitive outcomes is another hurdle in researching the connection between water pollution and children's educational outcomes[2]

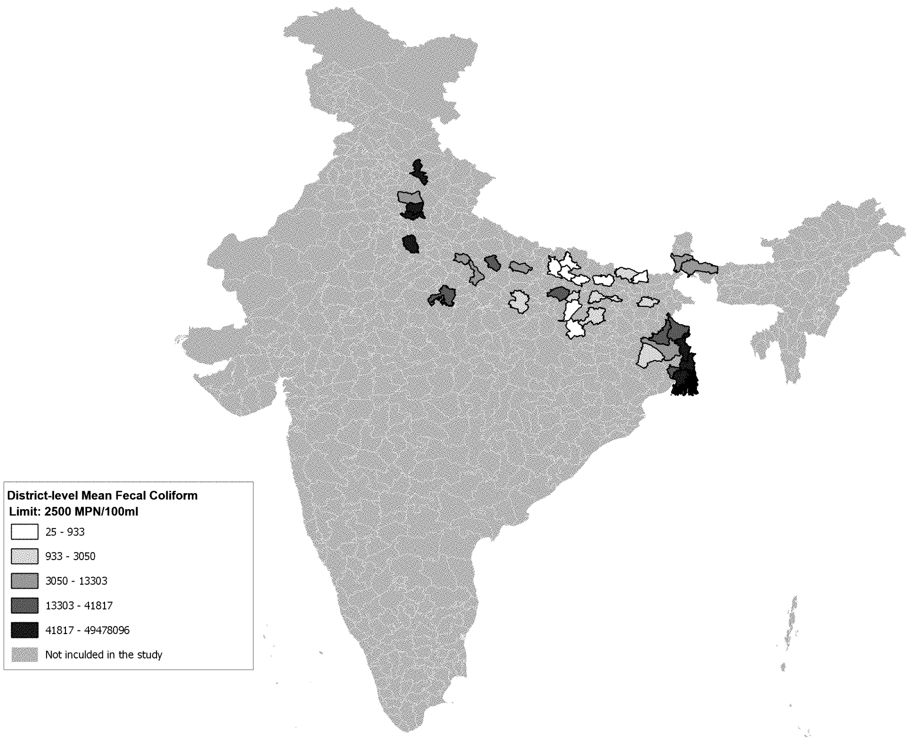
Our research question investigates whether unsafe levels of faecal coliform and Nitrate-N + Nitrite-N impair cognitive abilities in children residing in districts of the Ganges basin, near the Ganges, Yamuna, or one of their tributaries. The pollutants of interest are quantified as the district-level average of monitoring station readings within each district. Our study contributes to the literature in four significant ways. First, it is among the few studies to show the negative impact of water pollution on educational outcomes in the context of India. Second, from a policy perspective, the study suggests that any estimation of the social cost of poor water quality, which only considers the loss of public health and environmental damage, underestimates the true social cost by failing to account for the loss of human capital or decrease in educational outcomes. Third, our findings support the physiological literature on the adverse effects of water pollutants on human cognitive abilities. Lastly, our study enables a comparison among the effects of various water quality indicators on educational outcomes.

2 Data

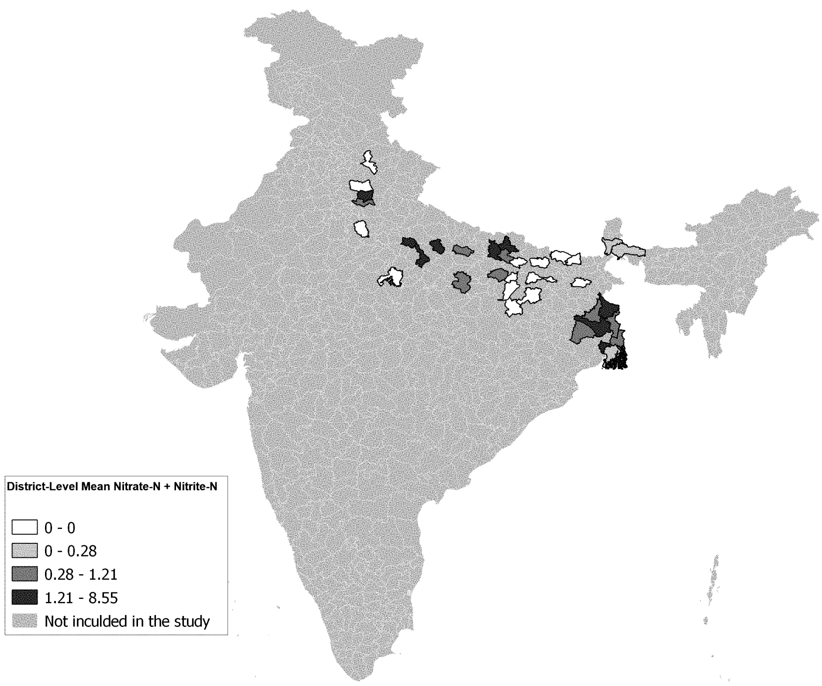
To examine the relationship between the water quality of the river Ganges and children's educational outcomes, we merge two types of data: (1) household survey data, which provides information on children's educational outcomes, and (2) water quality data, encompassing various measures of water quality[3]. Below, we detail both data sources and describe the variables employed to estimate our empirical model.

[2]Despite India's long history of environmental protection laws, such as the Water (Prevention and Control of Pollution) Act of 1974, the Air (Prevention and Control of Pollution) Act of 1981, and the Environment (Protection) Act of 1986, the country has continued to face challenges in reducing pollution. The Central Pollution Control Board (CPCB) and the State Pollution Control Boards (SPCBs) were established, and the government of India has adopted several environmental protection regulations over the past few decades. A landmark verdict by the Supreme Court in 1984, known as M.C. Mehta vs. Union of India, significantly reduced Ganges pollution and led to a decrease in the neonatal mortality rate (Do et al., 2018). This case marked the beginning of various initiatives aimed at cleaning the river. Following this, in 1985, the Ganga Action Plan was initiated to control water pollution in the Ganges, and it was subsequently expanded into the National River Conservation Plan (NRCP), encompassing other rivers in India. However, the lack of stringent enforcement of pollution regulations has made it challenging for the government to maintain pollution levels below the prescribed standards in many regions of India (Greenstone and Hanna, 2014).

[3]District names serve as the common geographic identifiers between these two data sources.



(a) Mean faecal Coliform



(b) Mean Nitrate-N + Nitrite-N

Figure 2: Mean faecal Coliform and Mean Nitrate-N + Nitrite-N in the Sample Districts

2.1 Indian Human Development Survey (IHDS)

The source of the household survey data for this paper is the Indian Human Development Survey (IHDS), a nationally representative dataset[4]. For this paper, we use the second round of the survey, conducted between November 2011 and October 2012. In this round, 42,152 households across 1,503 villages and 971 urban neighbourhoods throughout India were interviewed. While the first wave took place in the 2004-05 period, data from both the base year and the second round cannot be combined for this study because educational outcomes were only measured in the second round. Most children surveyed were at most two years old during the 2004-05 period and not suitable for educational aptitude testing. Data on various socioeconomic characteristics, such as individual health, household employment, and income, along with school facilities and staff, were collected. The interviews utilised two sets of questionnaires: one on income and social capital, typically answered by the male head of the household, and another on education and health, answered by an ever-married woman. The collected data are organised into fourteen modules, of which the Individual, Household, and School Facilities modules are used for this study[5]. After merging the data and excluding missing values, we retain 1,147 observations for children aged 8-11 living in 39 districts across 5 states in the Ganges Basin, where water quality was monitored[6].

2.2 Water Quality Data

We gathered water quality data for the districts in the Ganges basin for the years 2012 and 2013, drawing from the Central Pollution Control Board, (CPCB) (2012) database. This database operates under the Ministry of Environment, Forest, and Climate Change of the In-

[4]This dataset is made publicly available by Desai and Vanneman (2015). The IHDS is a biennial panel survey conducted by researchers at the University of Maryland in collaboration with the National Council of Applied Economic Research, New Delhi.

[5]Individual, Household, Eligible Women, Birth History, Medical Staff, Medical Facilities, Non-Resident, School Staff, School Facilities, Wage and Salary, Tracking, Village, Village Panchayat, Village Respondent.

[6]The merged data comprise 204,575 individual-level observations from 42,152 households. Of these individuals, 27,670 are under the age of 12. Maths, reading, and writing tests were administered to 11,749 individuals under 12. After removing around 100 missing values in control variables, we are left with 1,147 children in our analysis. These children reside in districts near the Ganges, Yamuna, or their tributaries within the Ganges Basin, where CPCB monitored various water sources.

dian Government[7]. The Central Pollution Control Board (CPCB) selects monitoring points along rivers or near water bodies (lakes and groundwater sources) that likely exhibit varying levels of key pollutants and potential turbidity. Monitoring points within districts along a river are sometimes categorised as either upstream or downstream from well-known locations. With each monitoring point's specific location provided, we identify the nearest district to each point. For instance, if a monitoring point is located in a river, we assign it the district situated directly on the riverbank. Most districts in our sample are located by a river, on the banks of the Ganges and/or Yamuna, or along their tributaries[8].

Pollution data was collected quarterly and monthly at these monitoring points, with CPCB publishing yearly averages for minimum, mean, and maximum levels of each water quality indicator. For example, at a specific monitoring point j at time $t = 1$, the CPCB calculates the minimum, mean, and the maximum levels of faecal coliform, $F_{max,1,j}$, $F_{mean,1,j}$, $F_{min,1,j}$, respectively. By averaging these measurements over total T periods, they create $\sum_{t=1}^{T} F_{max,t,j}/T$, $\sum_{t=1}^{T} F_{mean,t,j}/T$, and $\sum_{t=1}^{T} F_{min,t,j}/T$. If a district has J monitors - monitor index being $j = 1,2,3,...,J$ - and if data was collected by CPCB at T times in 2012, then we calculate the district mean as $\sum_{j=1}^{J}\sum_{t=1}^{T} F_{mean,t,j}/(T \times J)$. We use this averaging scheme for each district. Compared to the average maximum and minimum levels of pollution exposure, represented by $\sum_{j=1}^{J}\sum_{t=1}^{T} F_{max,t,j}/(T \times J)$ and $\sum_{j=1}^{J}\sum_{t=1}^{T} F_{min,t,j}/(T \times J)$ respectively, the overall mean pollution level $\sum_{j=1}^{J}\sum_{t=1}^{T} F_{mean,t,j}/(T \times J)$ more accurately indicates the level of pollution to which the sample respondents were most commonly exposed. The minimum and maximum readings from the monitoring points may reflect infrequent dips and spikes in pollution, not necessarily representing the regular exposure levels for children. Since the frequency of the maximum and minimum readings is not provided, we use only the mean pollution levels from the monitoring points to calculate $\sum_{j=1}^{J}\sum_{t=1}^{T} F_{mean,t,j}/(T \times J)$, the district-level pollution measure. District-level means of the other water quality variables have been calculated in the same way.

[7]Total coliforms organism and faecal coliform are very similar indicators. We only use faecal coliform in this study.

[8]Five districts in our sample had the Ganges or Yamuna flowing through them. In two districts, Jhansi and Gaya, the CPCB monitored only groundwater and lake water.

We primarily use water quality data from 2012, supplementing it with 2013 data to fill any gaps. Missing readings for certain monitoring points in 2012 could potentially bias the computation of average water quality variables. To address this, we impute missing values using their 2013 counterparts. We found that readings from monitoring points available in both years were consistent, with no cases of monitors shifting from benign pollution levels in 2012 to hazardous levels in 2013. Therefore, we are confident that our approach to handling missing data ensures the reliability and representativeness of the actual pollution levels.

2.3 Descriptive Statistics

Table 1 displays mean values for key variables, with each column representing a sample based on the type of water source monitored for pollution. For instance, the averages in the first column are derived from data on children in districts where river water was monitored. Column 7, in Table 1, shows variable means for the full sample of 1,147 children. In some districts, more than one type of water source was monitored. According to Columns 1 and 2 in Table 1, mean faecal conform and mean Nitrate-N + Nitrite-N levels are higher in the 'river' and 'Ganges' samples compared to 'Yamuna', 'groundwater' (GW), and 'Tributaries' (Trib.). The main binary variables of interest are district-average 1[Mean faecal Coliform > 2500 MPN/100 ml] and 1[Mean Nitrate-N + Nitrite-N > 1 mg/1L]. For simplicity and to save space, we express these variables as $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$ using Iverson notation, respectively[9].

Table 1 displays significant variations in the average values of water pollution measures. For example, the highest mean faecal coliform level is observed in the 'Lake' sample, while the 'Ganges' sample records the highest mean levels of Nitrate-N + Nitrite-N. Conversely, the

[9]The bars over FCOLI and NIT denote that they represent means. The term 'limit' is used to indicate their respective safe levels. Both variables indicate if the respective pollution amounts are above individual acceptable limits. Central Pollution Control Board (CPCB), India (2012) sets the acceptable limit of faecal coliform at 2500 MPN/100 ml. MPN means "most probable number". Its limit is set at 2500 MPN/100 ml by Central Pollution Control Board (CPCB), India (2012). They inspected whether, in 100 millilitres of water, the most probable count of coliform colonies was above 2500. The data from Central Pollution Control Board, (CPCB) (2012) does not include a limit for NITRATE- N+ NITRITE-N (mg/l). A report from the World Health Organisation provides separate safety limits for Nitrate-N and Nitrate-N, which are 10mg/l and 1mg/l, respectively. *Hardness in Drinking-water: Background document for development of WHO guidelines for drinking-water quality* (2010) is published by the World Health Organisation. Using the 1 mg/l limit, the more restrictive of the two limits, I create the binary indicator $1[\overline{NIT} > limit]$; the value 1 indicates the NITRATE-N + NITRITE-N level exceeds 1mg/1.

'Yamuna' sample, shown in Column (3), has the lowest levels of both mean faecal coliform and mean Nitrate-N + Nitrite-N, coinciding with the lowest mean test scores. These patterns indicate a possible link between higher district test scores and elevated levels of pollutants, possibly because urban districts, despite higher pollution, often have access to better educational resources and means to counteract water pollution effects. Hence, the descriptive data in Table 1 alone cannot comprehensively evaluate pollution's negative impact on test scores. A detailed analytical model is essential to pinpoint the impact of pollution exposure on test scores.

Our study focuses primarily on district-mean levels of faecal coliform and Nitrate-N + Nitrite-N as the main water pollutants, rather than on other pollutants for which data are available. Other water quality metrics, such as Biochemical Oxygen Demand (B.O.D.), Dissolved Oxygen Level (D.O.), and pH, are not classified as pollutants, though they do assess water quality[10]. We incorporate these metrics as control variables in our model. It is important to note that B.O.D. and D.O. levels do not consistently correlate with the levels of our primary pollutants of interest. Typically, higher B.O.D. levels and lower D.O. levels are observed in more turbid water, which may coincide with higher levels of faecal coliform and Nitrate-N + Nitrite-N (Ahipathy and Puttaiah, 2006). However, the absence of undesirable B.O.D. and D.O. levels does not necessarily mean the absence of unsafe levels of faecal coliform and Nitrate-N + Nitrite-N. For instance, Table 1 indicates that the groundwater' sample exhibits relatively fewer occurrences of undesirable B.O.D. and D.O. levels, yet the mean faecal coliform level in these districts is very similar to that of the full sample. In addition, in districts adjacent to the Yamuna River where B.O.D. levels exceed preferred thresholds, Nitrate-N + Nitrite-N levels do not reach hazardous levels. Thus, B.O.D. and D.O. levels do not always serve as accurate indicators of pollution. Lastly, the pH level exhibits minimal variation across the samples mentioned in Columns 1 to 7 of Table 1. All these samples, along with almost all districts in 'tributaries' and the full sample, maintain high but safe pH levels. Consequently, overall pH levels do not present a significant risk to the cognitive abilities of children.

[10]B.O.D indicates the oxygen consumed by microorganisms. When more microorganisms are present in the water, decomposing waste matter and propagating, dissolved oxygen levels decrease. Consequently, these two variables are highly correlated (Jouanneau et al., 2014)

In Table 1, individual characteristics such as age, gender, height, weight, and family consumption expenditure show only marginal variation across the monitored water source categories. Interestingly, the proportions of households with indoor piped water supply and those purifying water vary between 0.05-0.77 and 0.09-0.77, respectively. Handwashing after defecation is a critical preventive measure against many diseases (Curtis and Cairncross, 2003), and the proportion of households consistently practicing this varies narrowly from 0.69 to 0.77. Table A.2 represents variable means for samples that are exposed to unsafe level of faecal coliform and Nitriate-N + Nitrite-N. Table A.3 includes means of additional variables we use as controls. In the Online Appendix, we provide explanations of the table contents below the tables as needed.

For regression analysis, we employ binary measures of the water pollutants, $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$. Using binary variables offers three distinct advantages. First, they enable a clear distinction between the districts experiencing unsafe pollution levels and those that do not, based on the established safety limits for pollutant concentrations. Second, understanding the estimated effect of the binary variables that signal unsafe pollution levels in districts does not rely on pollution changing by a certain amount; there was not much difference in pollution levels from 2012 to 2013. Also, minute fluctuations, like a one MPN increase in faecal coliform in 100 ml of water, are unlikely to make noticeable differences in test scores, making the estimated effect of the one-unit hard to interpret. Lastly, identification of the effects of pollutants in a regression model can be challenging at extremely high values of the pollution-measuring continuous variables. This complexity arises because districts with the most significant river pollution are often both densely populated and economically advanced. It is easier for such districts to insure themselves against high levels of pollution by establishing superior water filtration systems.

We examine the educational outcomes of children living in Ganges Basin districts, focusing on areas where water sources were monitored for pollution. The survey assessed children's reading, writing, and arithmetic skills through tests administered to all eligible children aged 8-11 in each household. As indicated in Table 1, the test scores are considered continuous

Table 1: Analytical Sample Means of Key Variables

Variables	(1) River	(2) Ganges	(3) Yamuna	(4) Lake	(5) GW	(6) Trib.	(7) All
Mean faecal Coliform (MPN/100 ml) †	2.27	2.44	0.06	6.25	1.69	1.77	1.15
Mean Nitrate-N/Nitrite-N (mg/l)	1.13	1.22	0.34	0.49	1.05	0.65	0.89
Mean Biochemical Oxygen Demand (mg/l)	4.23	3.77	5.88	7.53	3.61	4.68	4.86
Mean Dissolved Oxygen (mg/l)	7.08	7.29	6.27	6.15	7.00	6.94	6.96
Mean pH	7.75	7.78	7.57	7.71	7.67	7.62	7.66
$1[Faecal\ Coliform > 2500MPN/100ml]$	0.84	0.83	1.00	0.84	0.68	0.59	0.72
$1[Nitrate-N+Nitrite-N > 1mg/l]$	0.22	0.24	0.00	0.18	0.35	0.30	0.27
$1[B.O.D > 3mg/l]$	0.57	0.53	1.00	0.63	0.40	0.33	0.43
$1[D.O. < 4mg/l]$	0.25	0.19	0.49	0.44	0.21	0.23	0.23
$1[pH < 6.5mg/l\ or\ pH > 8.5mg/l]$	1.00	1.00	1.00	1.00	1.00	0.95	0.96
Reading Test Z-Score	0.16	0.21	-0.12	0.32	0.19	0.13	0.13
Maths Test Z-Score	0.19	0.23	-0.09	0.45	0.26	0.21	0.20
Writing Test Z-Score	0.17	0.22	-0.12	0.43	0.22	0.18	0.16
Age	9.51	9.53	9.51	9.59	9.52	9.49	9.48
Sex - 1 if Male	0.49	0.50	0.53	0.55	0.52	0.53	0.52
1 [Majority Religious Group]	0.52	0.53	0.64	0.56	0.48	0.51	0.53
Anthropometry - height	128.06	128.15	129.00	126.43	126.60	126.32	127.13
Anthropometry - weight	25.73	25.87	25.30	26.36	25.63	25.17	25.32
1[HH per capita expenditure ≤ 25th ptile]	0.23	0.25	0.27	0.17	0.27	0.27	0.25
1[HH per capita expenditure ≤ 50th ptile]	0.45	0.46	0.48	0.39	0.53	0.54	0.50
1[HH per capita expenditure ≤ 75th ptile]	0.69	0.70	0.70	0.68	0.77	0.88	0.75
School Distance (kilometres)	1.56	1.57	1.66	1.99	1.56	1.53	1.57
School hours/week	30.73	30.73	33.64	27.7	29.40	29.44	30.13
Private Tuition hours/week	3.86	4.06	1.23	5.33	5.12	4.62	4.11
Books Uniform Cost (Rupees)	892.61	889.50	1026.96	996.14	657.36	734.91	844.25
Short-term Morbidity (days)	1.22	1.28	1.01	1.01	1.01	0.96	1.08
1[Water is purified in HH]*	0.10	0.11	0.05	0.15	0.09	0.77	0.09
1[HH has Indoor Piped Water Supply]	0.15	0.16	0.07	0.23	0.11	0.90	0.11
1[HH has Water Drinking Vessel]**	0.71	0.69	0.76	0.76	0.70	0.68	0.71
1[Always Handwash]***	0.75	0.72	0.76	0.77	0.75	0.69	0.72
N	576	532	155	206	769	738	1147

The Columns (1) to (5) present means of variables specific to groups of districts, defined by the types of water sources CPCB monitored for pollution in 2012: districts along Ganges and Yamuna rivers (col. 1), districts along the Ganges river only (col. 2), districts along the Yamuna river only (col. 3), districts where lake water was monitored (col. 4), districts where groundwater was monitored (col. 5), districts where water from tributary rivers of Ganges and Yamuna was monitored (col. 6), all districts (col. 7). 'River' and 'Tributaries' samples overlap, since tributaries are also rivers. However, in the 'river' sample, we include districts adjacent to major rivers, Yamuna and Ganges, which are not part of the 'tributaries' sample.

† Mean faecal Coliform (MPN/100 ml), reported in millions.

* Household purifies water by boiling, filtering, aquaguard, or chemicals.

** Household has water storage vessel.

*** Members of the households always wash hands after defaecation.

• pH measures the acidity or alkalinity of water, with the scale ranging from 0 to 14. Values below 7 are acidic, and values above 7 are alkaline. Water with very low or high pH may indicate chemical or heavy metal pollution (U.S. Geological Survey, 2021).

variables, with a comprehensive description provided in Table A.4[11]. These tests, developed in collaboration with researchers from PRATHAM[12], were pretested to ensure they were comparable across various languages. This method allows us to analyze the educational performance of school children in different states, accommodating the diverse languages used as mediums of instruction. Despite each Indian state having its unique school curriculum, PRATHAM's tests remain consistent across the board. The standardisation of test scores enables us to assess the impact of pollution exposure on children's average position within the test score distribution.

3 Empirical Model

The empirical model examines the effect of water quality on test scores (Equation 1). The analytical sample contains unique children $i = 1,2,3...n$ living in $k = 1,2,3,...,K$ districts.

$$Z_{ik} = \alpha_{ik} + W'\Theta + X'\Gamma + \chi_k + \varepsilon_{ik} \tag{1}$$

W is the vector of water quality variables W_k and they vary across districts. **X** is a vector of X_{ik} control variables and χ_k are district dummy variables. We use the same right-hand-side variables for each of the outcomes. Z_{ik} represents the outcome[13]

The main treatment variables, $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$, vary only between districts and not within each district. Our baseline model uses random intercept regression. ε_{ik} is the individual-level error term. Z_{ik} indicates our set of dependent variables are nested within cluster k, with each district representing a separate cluster. Since $1[\overline{FCOLI} > limit]$

[11] When adding more control variables to test the robustness of our primary estimates, treating scores as ordinal or binary variables causes convergence issues in multinomial logistic/probit model estimations. Similar to our method, studies by Chudgar and Quin (2012), Spears (2012), Vibhu and Ambrish (2015), and Singhal and Das (2019) also consider test scores as continuous in their OLS model estimations, indicating that this approach does not compromise the insights gained.

[12] The tests were available in multiple languages. PRATHAM is a non-governmental organisation that supports social science research. Further details can be found at PRATHAM (2021).

[13] The score levels of maths, reading, and writing tests correspond to different tasks of varying difficulty levels. For instance, maths level 2' indicates the child could solve subtraction problems, and level 3' suggests the child could tackle division problems.

and $1[\overline{NIT} > limit]$ vary across districts, we can interpret the coefficient estimates of these two variables as the average decline in a child's position within the test score distribution due to exposure to district-level water pollutants[14]. We include district-mean pH, and binary indicators of B.O.D. and D.O. in the vector W_k from 1[15].

The economic intuition behind applying the random-effects model is that the district-level errors are not necessarily affecting Z_{ik} through the variables of interest, W. Communities within a district can invest in water treatment plants and water supply networks to insure against pollution. More affluent districts, often more urbanised, tend to pool resources to develop better public water supply networks to mitigate water pollution risks (Sarker et al., 2021). Since water supply networks are monopolies requiring an initial fixed investment, and marginal cost of water supply to additional households is low, all the households in a district would have the same quality of water supply network available for them irrespective of individual household-level wealth and income. In other words, both rich and poor participate in the same water distribution network and are subject to similar levels of water quality. Thus, the unobserved heterogeneity due to a district's water supply characteristics of a district can be considered as random intercepts ($E(\mathbf{X}|\chi_k) = 0$) for the households and are not likely to drive (or be driven by) the household-level observed variables in $\mathbf{X}$. If $E(\mathbf{X}|\chi_k) \neq 0$ then we would need fixed-effects estimation of Equation 1. Therefore, we model district-level exposure to water quality as random district-level effects[16].

We prefer a random-effects model over one with district fixed effects because the fixed-effects model can introduce multicollinearity between the district-level dummy variables and the binary pollution variables. We run different tests to check if random-effects model should be used instead of some alternative models. Diagnostic tests developed by Hausman (1978) and

[14]For example, let us assume, $1[\overline{FCOLI} > limit]$'s estimated effect is statistically significant at -0.015 on maths test scores, this means that living in a district with unsafe levels of faecal coliform in its water sources causes the district's children to experience, on average, a drop of -0.015 standard deviations in their maths test score distributional position, effectively moving them to the left by 0.015 standard deviations in the score distribution.

[15]Only results in Tables 3, 4, and 5 include Mean B.O.D. Including both B.O.D and D.O measures in regression specifications results in these variables' coefficient estimates having ambiguous signs. To simplify, we include both Mean B.O.D. and Mean D.O. only in Tables 3, 4, and 5 to avoid confusion.

[16]In less-developed rural areas where (publicly funded) water supply networks are not established and water treatment plants are privately owned, the ability to insure against low water quality varies only at the community-level, not at the household level. We control for the the effect of this insurance ability using water-supply related controls in our model.

Schaffer and Stillman (2006), show that the random-effects model is preferred over the fixed-effects model[17]. Additionally, a test by Breusch and Pagan (1980) shows that the random-effects model is favoured over a simple Ordinary Least Squares (OLS) model. Furthermore, we conduct a Likelihood-Ratio (LR) test that indicate that a random-effects model is preferred to a pooled model with district dummy controls[18]. Overall, the results support applying a random intercept (district-level) specification.

The binary variables indicating unsafe levels of faecal coliform and Nitrate-N + Nitrite-N correlate with D.O., B.O.D., and pH to some degree, as they all reflect aspects of water quality. The exact functional relationships between them are unknown. Generally, water quality deteriorates when faecal coliform and Nitrate-N + Nitrite-N exceed safety limits. Consequently, the estimated effect of main water pollution measures may be overstated, capturing both the overall water quality impact and specific pollution contents. However, water turbidity is also associated with poor quality, making it essential to control for the effects of Mean B.O.D., Mean pH, and Mean D.O. in Equation 1. By doing so, we might have overly adjusted for water quality effects, rendering the estimates of the impact of unsafe levels of faecal coliform and Nitrate-N + Nitrite-N as 'lower-bound' estimates.

3.1 Identification

Equation 1 is based on the structure of a simple education production function. This function, widely discussed in the education economics literature, relates educational inputs to outcomes like test scores and class rankings (see Krueger, 1999; Pritchett and Filmer, 1999; Hanushek, 2010, 2020, among others). We assume that water quality levels are 'predetermined' factors in the education production process. Thus, the error term ε_{ik} is uncorrelated with water quality,

[17] Schaffer and Stillman (2006) provide a test for over-identifying restrictions in random-effects versus fixed-effects models. The fixed effects estimator relies on the orthogonality conditions that X_i are uncorrelated with the idiosyncratic error ε_{ik}, i.e., $E(X_{it} \times \varepsilon_{ik}) = 0$. The random effects estimator introduces additional orthogonality conditions that X_{ik} are uncorrelated with the group-specific error χ_k (the 'random effects'), i.e., $E(X_{ik} \times \chi_k) = 0$. These additional orthogonality conditions are over-identifying restrictions that we test. The results suggest considering a random-effects model.

[18] With three outcomes and multiple water source-specific samples (districts by lakes, districts by the Ganges, districts by Yamuna and Ganges tributaries, etc.), we conduct LR tests for each test score $\times$ water-source sample combination.

or $E(W_k|\varepsilon_{ik}) = 0$. While this is a strong assumption, we later introduce a propensity score matching model to estimate the causal effects of $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$ on test scores, relaxing this initial assumption.

River pollution is the outcome tied to economic activities, population density, and geographic characteristics of an area (Suthar et al., 2010). However, schooling is governed by state policies and government mandates in India, i.e. all children have to attend schools (Chhokar, 2010). The government provides funding to the schools, dictates school curricula and related policies (Weiner et al., 1991; Kingdon, 2007). The average quality of education and outreach at a district is not subject to the aggregate factors which may drive river pollution - overpopulation, urbanisation, and industrialisation. Average education outcomes of the children may be driven by river pollution and other aggregate factors. Pollution impacts education production through the channel of both short-term and long-term health, as health is directly linked to water quality and, consequently, to productive outcomes such as educational attainment.

The Central Pollution Control Board (CPCB) employs stringent criteria to select monitoring points, indicating a non-random selection process. Consequently, the non-random selection of monitoring stations leads to a non-random selection of districts in our analysis. To address this, we calculate district-level mean pollution after aggregating readings from all monitoring points in a district. If the sample distribution of pollutants is skewed right because Central Pollution Control Board (CPCB), India (2012) monitors more polluted areas, then the sample mean might exceed the true average pollution level. However, our focus is on binary indicators that show whether average monitored pollution levels exceed safety limits. Given that the sample includes districts with pollution levels below the unsafe threshold, it seems unlikely that Central Pollution Control Board (CPCB), India (2012) exclusively monitored the most polluted river sections. Furthermore, some monitors detected no faecal coliform and Nitrate-N + Nitrite-N levels, suggesting that the selection of monitoring sites is unlikely to compromise the validity of our findings on the pollutants' treatment effect.

For robustness checks, the vector X_{ik} in Equation 1 is expanded to include the effects of teaching quality, educational expenditure, schooling quality, short-term morbidity, use of technology, and household members' personal hygiene. Since we lack variables for long-term morbidity throughout the children's lives, which could be linked to river pollution, we use district-level short-term morbidity as a proxy. The decline in skills such as maths, reading, and writing cannot result from random sickness episodes alone. Short-term morbidity doesn't reveal the children's susceptibility to illness. Continuous consumption of poor-quality water, even if it doesn't cause immediate sickness, may lead to cognitive declines in children. The reading, writing, and maths tests administered by PRATHAM (2021) measure the students' average cognitive abilities. Therefore, mean district-level morbidity is intended to capture spikes in short-term morbidity due to unforeseen reasons and the overall health of children in the district, excluding the cognitive loss channel in children exposed to unsafe pollution levels in drinking water.

We investigate the possible channel of cognitive ability loss due to pollutant contents in drinking water. Thus, we further demonstrate that interaction terms between $1[\overline{FCOLI} > limit]$ and binary variables describing household water supply and storage choices are statistically significant. This analysis aims to identify how water pollutants, not removed by the water supply system—which may or may not have a filtration system—affect children's cognitive abilities[19].

Household characteristics such as the educational level of the head, available resources, and income significantly impact children's educational outcomes. Families with well-educated heads, ample resources, and higher incomes often see better educational results for their children. However, when considering the substantial impact of high water pollution levels on education and income, children from households with lower educational outcomes may become trapped in a cycle of poverty. These children may face challenges in earning low incomes and lack the means to relocate from areas with poor water quality. In such a scenario, the current household head's lower investment in children's education might be linked to lower investment (P_k) in his/her education when he/she was a child and therefore, $E(P_k|\varepsilon_{ik}) \neq 0$. In addition, the

[19]While we account for the effects of district-level short-term morbidity, this channel could receive mixed effect from other externalities associated with river pollution. For instance, consuming fish from a polluted river could also impair children's cognitive functions in the long term (Singh and Soma, 2014). Another potential externality is the use of polluted water for irrigation, which might bypass the water supply system and affect health (Lu et al., 2015; Nagpoore et al., 2020).

observational data used here does not include individual or household-level instruments that could be used to infer causation between poor water quality and educational outcomes.

We define a binary treatment variable T_f in the following way.

$$T_f = \begin{cases} 1 & \text{if } faecal\ coliform > \text{limit} \\ 0 & \text{otherwise} \end{cases}$$

Therefore, we estimate "Average Treatment Effect on the Treated" (ATT), which measures the difference between expected test scores of children in high-pollution districts $T_f = 1$ versus a counterfactual outcome expressed as:

$$ATT_f = E[Z_1 - Z_0|T_f = 1] = E[Z_1|T_f = 1] - E[Z_0|T_f = 1] \tag{2}$$

In Equation 2, Z_0 and Z_1 are outcomes of the non-treated ($T_f = 0$) and the treated ($T_f = 1$). The subscript f expresses that the treatment is unsafe levels of faecal coliform. $E[Z_0|T_f = 1]$ is the counterfactual state that we do not observe and estimate. By extension, the average treatment effect on the treated is also applicable for unsafe levels of Nitrate-N + Nitrite-N. If T_n holds 1 for district-level mean Nitrate-N + Nitrite-N to be over the safe level, and 0 otherwise, then $ATT_n = E[Z_1 - Z_0|T_n = 1] = E[Z_1|T_n = 1] - E[Z_0|T_n = 1]$. The subscript n expresses that the treatment is unsafe levels of Nitrate-N + Nitrite-N. Identification is dependent on the assumption of conditional independence - if we control for the household and individual factors that drive educational outcomes, then the treatment effect can be considered random. For this non-experimental exercise, we use the widely-known propensity score matching (PSM) developed by Rosenbaum and Rubin (1983).[20]

[20]We implement propensity-score matching using the algorithm described in Chapter 24 of Cameron and Trivedi (2022).

4 Results

The baseline regression results are in Tables 3, 4, and 5. These three tables present the estimated coefficients associated with the river pollution variables. The baseline regression model also includes control variables related to (1) individual characteristics of the children like age, sex, height, weight; (2) household characteristics, (3) schooling-related information, (4) household water sources and basic hygiene, and short-term morbidity.

The baseline regression results in Tables 3, 4, and 5 can be combined to provide a picture of the negative impact of river pollution on children's test outcomes. Column 1 results are estimated using the full sample in each of the three Tables. The pollutants do not appear to generate a statistically significant effect on the test scores which are based on the full sample. Only for the 'river' and the 'Ganges' samples, we see unsafe levels of faecal coliform generating a statistically significant negative impact[21]. The largest impact of faecal coliform is on writing test and the smallest on reading when the samples, 'river' and the 'Ganges' are considered (Columns 1 and 5 in Tables 3, 4, and 5). Overall, faecal coliform has a negative impact on test outcomes. Unsafe levels of Nitrate-N + Nitrite-N only has a significant impact on reading tests when 'groundwater' districts are considered. Among other variables, age, height, and weight have some estimated positive impact on the test scores as expected. Binary indicators of household consumption is coded 1 if per-capita consumption expenditure of a household is at the 25th, 50th, and 75th percentile of the distribution or below. As the reference group is children from households above the 75th percentile of the per-capita consumption expenditure distribution, the estimated effects of these variables, when statistically significant, understandably are negative.

Having an indoor piped water supply is also estimated to have a positive impact on children's reading test scores (Column 1, and 3 to 6 in Table 3), and also on Maths and Reading test scores (Column 6 in Table 4 and in Table 5). In districts adjacent groundwater and tributaries that were monitored for pollution, the effect of unsafe levels of faecal coliform and Nitrate-N

[21] We want to remind the readers that Central Pollution Control Board (CPCB) of India monitored groundwater and lakes in some districts. We consider all districts where any water source is monitored and which are in states through which the river Ganges, Yamuna, and their tributaries flow through.

Table 3: Baseline Regression - The Effect of Water Pollution on Reading Test Score

	(1) Reading Score	(2) Reading Score	(3) Reading Score	(4) Reading Score	(5) Reading Score	(6) Reading Score
AGE	0.0949	0.122	0.0980	0.0908	0.0913	0.120
	(0.0252)	(0.0597)	(0.0354)	(0.0253)	(0.0356)	(0.0318)
FEMALE	0.00724	0.0586	0.0229	0.0144	0.0138	0.0154
	(0.0479)	(0.0641)	(0.0856)	(0.0596)	(0.0796)	(0.0519)
HEIGHT	0.00275	0.00138	-0.00244	0.00117	-0.00141	0.000889
	(0.00272)	(0.00562)	(0.00428)	(0.00233)	(0.00448)	(0.00257)
WEIGHT	0.0140	0.00848	0.0198	0.0154	0.0221	0.0128
	(0.00514)	(0.00915)	(0.00613)	(0.00562)	(0.00638)	(0.00670)
HH Con.$\leq$ 75th ptile.	-0.0125	0.216	-0.0561	0.0953	-0.0305	0.0147
	(0.0720)	(0.0963)	(0.114)	(0.111)	(0.103)	(0.103)
HH Con.$\leq$ 50th ptile.	-0.0965	-0.357	-0.150	-0.116	-0.168	-0.0951
	(0.0673)	(0.139)	(0.0982)	(0.106)	(0.0930)	(0.132)
HH Con.$\leq$ 25th ptile.	-0.278	-0.196	-0.294	-0.286	-0.198	-0.285
	(0.0680)	(0.136)	(0.0814)	(0.132)	(0.109)	(0.137)
INDOOR PIPED WATER	0.225	0.101	0.244	0.241	0.261	0.288
	(0.0882)	(0.123)	(0.0955)	(0.114)	(0.0996)	(0.137)
$1[\overline{FCOLI} > limit]$	-0.129	-0.749	-0.234	-0.0689	-0.245	-0.0578
	(0.0933)	(0.313)	(0.115)	(0.134)	(0.124)	(0.0814)
$1[\overline{NIT} > limit]$	-0.0812	-0.0459	-0.0650	-0.193	-0.119	-0.140
	(0.104)	(0.103)	(0.170)	(0.0607)	(0.172)	(0.0999)
$1[\overline{D.O.} < threshold]$	-0.0752	-0.0169	0.131	-0.171	0.0688	-0.0318
	(0.0987)	(0.327)	(0.0896)	(0.203)	(0.138)	(0.165)
Mean B.O.D	0.00291	0.00647	0.0190	0.0312	0.00126	0.00130
	(0.00434)	(0.00925)	(0.00805)	(0.0233)	(0.0255)	(0.00375)
Mean pH	-0.160	-1.603	-0.171	-0.167	0.0684	-0.233
	(0.123)	(0.613)	(0.109)	(0.197)	(0.177)	(0.198)
N	1147	206	532	769	576	738
Overall R^2	0.27	0.33	0.30	0.53	0.31	0.51
Sample	All	Lake	Ganges	GW	River	Trib.

Robust standard errors clustered at district level in parentheses. FCOLI = Faecal Coliform and NIT = Nitrate-N + Nitrite-N

- HH Con. = Household Consumption per capita. ptile = perccentile. GW = groundwater. Trib. = Tributaries.
- **Pollutants**: **FCOLI** = faecal Coliform; **NIT** = Nitrate-N + Nitrite-N; **D.O.** = Dissolved Oxygen; **Mean B.O.D.** numerical, mean Biochemical Oxygen Demand; **Mean pH** numerical, Mean pH level.
- **Explanatory variables not reported** : Numerical variables such as "hours spent at school per week", "hours spend doing homework per week", "hours spent being tutored per week", "distance from school to home", "number of days the child spent disabled because of short-term morbidity in the last 30 days". Binary Variables such as "Rupees spent on books and uniform > Rs. 500", "1 = water storage vessel available at home", "1 = water is purified at home though some mode of filtration or boiling", "1 = household members always wash hands after defaecation".

Table 4: Baseline Regression - The Effect of Water Pollution on Maths Test Score

	(1) Score	(2) Score	(3) Score	(4) Score	(5) Score	(6) Score
AGE	0.0667	0.0231	0.0999	0.0689	0.0875	0.0653
	(0.0256)	(0.0411)	(0.0468)	(0.0325)	(0.0448)	(0.0241)
FEMALE	-0.0685	0.0543	-0.0294	-0.0553	-0.0306	-0.0458
	(0.0414)	(0.154)	(0.0783)	(0.0643)	(0.0753)	(0.0719)
HEIGHT	0.00394	0.0149	-0.000741	0.00267	0.000194	0.00473
	(0.00281)	(0.00295)	(0.00427)	(0.00353)	(0.00406)	(0.00329)
WEIGHT	0.0148	0.00479	0.0222	0.0124	0.0241	0.0130
	(0.00645)	(0.00700)	(0.00659)	(0.00884)	(0.00623)	(0.00891)
HH Con.$\leq$ 25th ptile.	-0.259	-0.474	-0.370	-0.259	-0.273	-0.226
	(0.0898)	(0.203)	(0.0675)	(0.127)	(0.0988)	(0.131)
HH Con.$\leq$ 50th ptile.	-0.0245	-0.0155	-0.0206	-0.0489	-0.0365	-0.0000922
	(0.0969)	(0.127)	(0.150)	(0.128)	(0.137)	(0.141)
HH Con.$\leq$ 75th ptile.	-0.246	-0.115	-0.379	-0.250	-0.315	-0.238
	(0.0919)	(0.133)	(0.152)	(0.106)	(0.144)	(0.0976)
INDOOR PIPED WATER	0.138	0.169	0.0510	0.158	0.0687	0.220
	(0.0896)	(0.227)	(0.140)	(0.106)	(0.133)	(0.0799)
$1[\overline{FCOLI} > limit]$	-0.146	-0.669	-0.322	-0.0913	-0.342	-0.131
	(0.128)	(0.311)	(0.132)	(0.126)	(0.138)	(0.0911)
$1[\overline{NIT} > limit]$	-0.0493	0.112	0.0868	0.0168	0.0282	-0.0912
	(0.160)	(0.175)	(0.107)	(0.114)	(0.111)	(0.127)
$1[\overline{D.O.} < threshold]$	-0.0545	-0.0524	0.115	-0.137	0.0611	0.00650
	(0.163)	(0.357)	(0.167)	(0.230)	(0.156)	(0.189)
Mean B.O.D.	0.000479	0.000237	0.0123	0.0176	-0.00489	-0.00351
	(0.00391)	(0.0117)	(0.0161)	(0.0237)	(0.0285)	(0.00374)
Mean pH	-0.372	-1.468	-0.335	-0.326	-0.111	-0.488
	(0.196)	(0.484)	(0.178)	(0.262)	(0.238)	(0.172)
N	1147	206	532	769	576	738
Overall R^2	0.28	0.56	0.34	0.27	0.33	0.26
Sample	All	Lake	Ganges	GW	River	Trib.

Robust standard errors clustered at district level in parentheses.

- HH Con. = Household Consumption per-capita. ptile = percentile. GW = groundwater. Trib. = Tributaries.
- **Pollutants**: **FCOLI** = faecal Coliform; **NIT** = Nitrate-N + Nitrite-N; **D.O.** = Dissolved Oxygen; **Mean B.O.D.** numerical, mean Bio-chemical Oxygen Demand; **Mean pH** numerical, Mean pH level.
- **Explanatory variables not reported**: Numerical variables such as "hours spent at school per week", "hours spend doing homework per week", "hours spent being tutored per week", "distance from school to home", "number of days the child spent disabled because of short-term morbidity in the last 30 days". Binary Variables such as "Rupees spent on books and uniform > Rs. 500", "1 = water storage vessel available at home", "1 = water is purified at home though some mode of filtration or boiling", "1 = household members always wash hands after defaecation".

+ Nitrite are statistically indistinguishable from zero[22]. We investigate whether the interaction between unsafe levels of faecal coliform and access to indoor piped water supply significantly affects test scores. While indoor piped water alone has minimal impact on scores, Column 6, Table A.5 reveals that in the 'river' sample, the positive effect of indoor piped water (+0.818) on writing scores is nearly cancelled out by its interaction with the faecal coliform variable (-0.803). This suggests that faecal coliform may impair children's cognitive abilities, as reflected in test scores, despite the presence of indoor piped water supply. Results in columns 3 and 5 in Table 4 are based on 'Ganges' and 'groundwater' samples. Tables 3, 4, and 5 support that the impact of unsafe levels of faecal coliform is primarily driven by the pollution in the river Ganges. Our other binary variable of interest about Nitrate-N + Nitrite-N has an only significant impact on reading test scores when the districts where groundwater is monitored are chosen.

We look for heterogeneity in the estimated effect of $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$ between genders. Looking for differential pollution effect on boys versus girls, we find that $1[\overline{FCOLI} > limit]$ has approximately 0.01 standard deviations greater effect on boys than girls in writing tests (Column 9 and Column 12 in TableA.6). We check if the effect $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$ differ across states. We find the more economically developed West Bengal sees greater negative impact of $1[\overline{FCOLI} > limit]$ on Writing tests compared to Uttar Pradesh and Bihar-Jharkhand sample (Columns 6 and 9 in Table A.10)[23].

Caste-based and religion-based discrimination in accessing safe water suggests that water pollution's impact might vary across different castes and religious groups (Hoff, 2016). However, dividing the sample by religion and caste results in too few observations per group, leading mostly to inconclusive results and hindering our ability to detect potential heterogeneity in the effects of $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$. Given the distinct social statuses and relationships among the six religious and caste groups, merging these groups to enlarge sample sizes could lead to misleading conclusions.

[22]We cannot provide estimates separately for the districts adjacent to the river Yamuna where its water was tested for pollution because Nitrate-N + Nitrite-N and faecal coliform have no variation for those districts.

[23]In this Table, the coefficient for $1[\overline{NIT} > limit]$ for the sample of West Bengal is not identified as it has no variations in that state.

Table 5: Baseline Regression - The Effect of Water Pollution on Writing Test Score

	(1) Score	(2) Score	(3) Score	(4) Score	(5) Score	(6) Score
AGE	0.0951	0.0429	0.114	0.106	0.103	0.128
	(0.0281)	(0.0541)	(0.0434)	(0.0313)	(0.0421)	(0.0374)
FEMALE	0.0536	0.140	0.0266	0.0717	0.00104	0.101
	(0.0348)	(0.0829)	(0.0607)	(0.0424)	(0.0609)	(0.0478)
HEIGHT	0.00206	0.00317	0.00217	0.00367	0.00342	0.00103
	(0.00278)	(0.00819)	(0.00399)	(0.00256)	(0.00408)	(0.00313)
WEIGHT	0.00759	0.0120	0.00544	0.00378	0.00820	0.00161
	(0.00507)	(0.00883)	(0.00724)	(0.00525)	(0.00775)	(0.00614)
HH Con.$\leq$ 25th ptile.	-0.326	-0.586	-0.344	-0.280	-0.261	-0.288
	(0.0952)	(0.294)	(0.0985)	(0.123)	(0.123)	(0.127)
HH Con.$\leq$ 50th ptile.	-0.0394	-0.0116	-0.168	-0.0335	-0.153	-0.0539
	(0.0613)	(0.190)	(0.0968)	(0.0912)	(0.0869)	(0.0858)
HH Con.$\leq$ 75th ptile.	-0.0342	0.0235	-0.132	-0.0278	-0.0577	0.0335
	(0.0865)	(0.138)	(0.0736)	(0.104)	(0.0898)	(0.132)
INDOOR PIPED WATER	0.168	-0.0467	0.0863	0.125	0.104	0.339
	(0.0888)	(0.140)	(0.110)	(0.114)	(0.103)	(0.126)
$1[\overline{FCOLI} > limit]$	-0.170	-0.341	-0.351	0.00234	-0.364	-0.0119
	(0.110)	(0.326)	(0.178)	(0.136)	(0.183)	(0.154)
$1[\overline{NIT} > limit]$	0.109	-0.0870	0.0851	0.00774	0.0307	0.0798
	(0.149)	(0.206)	(0.172)	(0.0932)	(0.186)	(0.136)
$1[\overline{D.O.} < threshold]$	-0.137	-0.116	-0.0176	-0.218	-0.0700	-0.147
	(0.107)	(0.377)	(0.142)	(0.110)	(0.162)	(0.127)
Mean B.O.D.	0.00236	0.0156	0.0183	0.0175	0.00139	0.000363
	(0.00280)	(0.0112)	(0.00758)	(0.0220)	(0.0249)	(0.00248)
Mean pH	-0.111	-0.627	-0.125	0.0458	0.108	-0.233
	(0.0948)	(0.520)	(0.138)	(0.174)	(0.177)	(0.155)
N	1147	206	532	769	576	738
Overall R^2	0.20	0.31	0.26	0.31	0.44	0.23
Sample	All	Lake	Ganges	GW	River	Trib.

Robust standard errors clustered at district level in parentheses.

- HH Con. = Household Consumption per capita. ptile = perccentile. GW = groundwater. Trib. = Tributaries.
- **Pollutants**: **FCOLI** = faecal Coliform; **NIT** = Nitrate-N + Nitrite-N; **D.O.** = Dissolved Oxygen; **Mean B.O.D.** numerical, mean Biochemical Oxygen Demand; **Mean pH** numerical, mean pH level.
- **Explanatory variables not reported** : Numerical variables such as "hours spent at school per week", "hours spend doing homework per week", "hours spent being tutored per week", "distance from school to home", "number of days the child spent disabled because of short-term morbidity in the last 30 days". Binary Variables such as "Rupees spent on books and uniform $>$ Rs. 500", "1 = water storage vessel available at home", "1 = water is purified at home though some mode of filtration or boiling", "1 = household members always wash hands after defaecation".

In Table 6, we present average treatment effect on the treated (ATT) by estimating a propensity-score matching model outlined in Equation 2. The estimated ATT shows causal impact of the main pollution treatments. The results show that when the full samples are considered, T_f has a statistically significant causal impact on reading, maths, and writing score. T_n also has a negative impact on reading and maths score.

Table 6: Average Treatment Effect on the Treated

	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
T_f (1 vs. 0)	-0.0882	-0.265	-0.143			
	(0.0412)	(0.0762)	(0.0120)			
T_n (1 vs. 0)				-0.314	-0.256	-0.119
				(0.0648)	(0.0825)	(0.0844)
N	1147	1147	1147	1147	1147	1147

- Abadie and Imbens (2016) robust standard errors in parentheses.
- T_f = 1 means that the household is in district that received the treatment of exposure to unsafe levels of faecal coliform and T_f =0 means untreated. T_n = 1 means that the household is in district that received the treatment of exposure to unsafe levels of Nitrate-N + Nitrite-N and T_n =0 means untreated.
- Average treatment effect on the treated has been estimated by propensity-score matching. We consider a logit treatment model. Conditioning variables in the treatment model: Demographic identities, age, height, weight, consumption expenditure by households, and individual-level variables: household per-capita income, school distance, school hours/week, homework hours/week, private tuition hours/week, expenditure on books and uniform, short-term morbidity (days of disability in the previous thirty days before the survey interview), Binary: whether the household boils water for purification (1=yes), whether household members wash hands after defaecation (1=yes).

4.1 Robustness Checks

We check the robustness of the effects of the pollutants in several ways. In the first, we include more variables in $X'_{ik}\Gamma$ that cover more factors related to individual characteristics, household characteristics, water source information, short-term morbidity, and schooling[24]. The results in

[24] The additional control variables provide comprehensive information. We include dummy variables for school types (e.g., EGS, Government, Government-aided, Private, Convent, Islamic school or 'Madrassa', Other/Open School) to indicate the child's current standard, year, or grade. Binary control variables capture whether the child receives a free uniform or books from school, whether the government covers the child's school fees, the scholarship amount received by the child, and the household's expenditure on the child's bus fare. Additionally, we incorporate control variables related to technology usage, such as ownership of a mobile phone, computer usage, and computer knowledge by the household respondent. Moreover, we account for short-term morbidity by including variables for total related costs in the last 30 days (inpatient/outpatient, e.g., doctor, hospital, surgery), the number of days the child was ill, costs for medicines/tests not covered by doctor/hospital fees, travel costs for treatment, and occurrences of cough or fever in the child within the last 30 days.

Tables A.11 show if the effects of $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$ on reading and writing are robust even after the inclusion of a long list of control variables. The results in Table A.12 are estimated by adding indicators related to teaching quality to the regression specification in addition to the set of explanatory variables corresponding to the results in Table A.11[25]. The estimated effect of $1[\overline{FCOLI} > limit]$ on reading and writing scores is still robust in Table A.12.

As a sensitivity analysis, we estimate the baseline results using mixed-model specifications, where the random-effects is interpreted as district-specific random intercepts (Table A.13). The estimated effect of $1[\overline{FCOLI} > limit]$ in Table A.13 are similar to those in Tables, 3, 4 and 5, proving that these alternative specifications do not change the baseline results. In addition, the Tables A.14 and A.15 exhibit the statistically robust effects of $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$, respectively employing two-level and three-level random-intercept models that account for variations within villages, neighbourhoods, and households. In Table A.16, we find that after including a measure of short-term morbidity, the effects of $1[\overline{FCOLI} > limit]$ on reading scores in the 'river' sample and $1[\overline{NIT} > limit]$ on reading scores in the full sample remain robust statistically. Next, after adding state-specific controls to our regression specifications, we find that the effect of $1[\overline{NIT} > limit]$ loses its statistical significance but the effect of $1[\overline{FCOLI} > limit]$ remains statistically robust on the three test scores for the full sample (Table A.17). We attempt to separate seasonality effect from the pollution effect in Table A.18. As our dataset is of cross-sectional nature, we plug $State\ ID \times Disctrict - Mean\ Morbidity \times Survey\ Month$ - interaction terms - in the model which are supposed to account for variations in district-mean morbidity over the survey months, and find that the effect of $1[\overline{FCOLI} > limit]$ remains robust on reading and maths scores in the full-sample regression (Table A.18).

Besides water pollution, other types of pollution like land and air pollution, may also affect test scores. Increase in water and air pollution when driven by both rapid urbanisation can coincide, and the estimated effect of water pollutants can partially contain the effect of air

[25] Description of these variables can be found in Table A.3.

pollution. We have included PM2.5[26], a measure of air pollution, as a control variable in our model. PM2.5 refers to particulate matter in the air that are less than 2.5 micrometers in diameter. We find that the impact of $1[\overline{FCOLI} > limit]$ on reading and maths scores remain statistically significant in the full sample in Table A.19. Moreover, its influence on writing scores also proved to be statistically significant in districts near Ganges.

Our final robustness checking strategy instruments the district-mean level of faecal coliform with the district's upstream adjacent district's mean level of faecal coliform ($MeanFCOLI$). This instrumentation is based on the idea that pollution from an upstream district generate exogenous variation in its downstream neighbouring district; the upstream district is not likely to be influenced by downstream conditions. The instrumented $MeanFCOLI$ on reading scores across three different samples: full sample, 'river', and 'tributaries' sample in Table A.20.

'Explanation for Table A.20' includes the instrumentation strategy. We also observe weaker effect of the instrumented $MeanFCOLI$ on the maths score in the full sample and the 'tributaries' sample but not on the writing score, potentially due to a smaller number of observations available. Notably, in 'tributaries' sample, the coefficients for district $MeanFCOLI$ remain unchanged between random-effects and Generalised 2SLS random-effects model (Columns 13 to 18, A.20). This instrumental variable analysis, leveraging upstream faecal coliform levels, acts as an additional robustness check, supporting our primary findings.

5 Conclusion

This study focuses on the impact of water pollution on the educational outcomes of school-going children aged 8-11 across 39 districts in the Ganges Basin of India. Water, as a crucial natural resource for production and consumption, can have long-term effects on human health,

[26]PM2.5, also known as particulate matter 2.5, refers to tiny airborne particles with a diameter of 2.5 microns or less. These particles are commonly measured in micro-grams per cubic meter (µg/m³) to determine their concentration in the air. To ensure a safe and healthy environment, health regulations and standards are established to control and restrict the levels of PM2.5 present in the atmosphere. Presently, the WHO guidelines advocate for an annual average PM2.5 concentration of 5 micro-grams per cubic meter (µg/m³) of air (*WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*, 2021). Our records encompass the yearly mean PM2.5 data at the district level. We collect this data from "Air Quality Life Index Database" (2023)

life expectancy, and cognitive functions through various channels. Using data from the Centre for Pollution Control Board of India (CPCB) and the Indian Human Development Survey (IHDS) 2011-12, we estimate water pollution effect on performance in three tests taken by children aged 8-11 as part of the IHDS. We find that unsafe faecal coliform levels have a consistently robust negative effect on reading and writing test scores. In several extended specifications and sensitivity analyses, the impact of faecal coliform on maths scores was not statistically robust. The negative effect of Nitrate-N + Nitrite-N was statistically indistinguishable from zero in some robustness checks. The negative effects of faecal coliform in water sources on children's reading and writing performance prove to be consistently significant, even when controlling for additional factors such as average district-level short-term morbidity in children (over thirty days), quality of teaching, and adjustments made using a propensity-score matching model. This suggests that faecal coliform contamination may impair the cognitive development of children exposed to poor water quality through the channel of health deterioration for prolonged periods (exceeding thirty days). Future studies, employing larger datasets and more precisely pinpointed water pollution data, have the potential to refine our understanding of how water contaminants like faecal coliform and Nitrate-N + Nitrite-N impact cognitive functions.

Declaration of Competing Interests

The authors declare none.

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Data Availability Statement

Data from the Indian Human Development Survey are openly available at Inter-university Consortium for Political and Social Research, Ann Arbor, Michigan, The United States (URL: https://doi.org/10.3886/ICPSR36151.v6).

The water quality data is derived from the publicly available source at URL: https://cpcb.nic.in/nwmp-data-2012/. This data is collected and maintained by Central Pollution Control Board (CPCB), Ministry of Environment, Forests and Climate Change, Government of India.

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Online Appendix

Table A.1: Districts with Unsafe Levels of Water Pollutants

District	(1) $1[\overline{FCOLI} > limit]$ District	(2) $1[\overline{NIT} > limit]$ District	(3) Obs.
Location			
Bihar - Purbi Champaran	1	1	49
Bihar - Madhubani	0	1	51
Bihar - Supaul	0	1	17
Bihar - Muzaffarpur	0	1	56
Bihar - Siwan	0	1	32
Bihar - Saran	0	1	7
Bihar - Bhagalpur	1	1	43
Bihar - Patna	0	1	10
Bihar - Buxar	1	1	11
Bihar - Rohtas	0	1	58
Bihar - Gaya	0	1	13
Uttar Pradesh - Muzaffarnagar	1	1	33
Uttar Pradesh - Meerut	1	0	11
Uttar Pradesh - Ghaziabad	1	0	28
Uttar Pradesh - Mathura	1	1	44
Uttar Pradesh - Budaun	0	1	17
Uttar Pradesh - Lucknow	1	0	12
Uttar Pradesh - Kannauj	1	0	23
Uttar Pradesh - Kanpur Nagar	1	0	47
Uttar Pradesh - Jhansi	1	1	16
Uttar Pradesh - Prayagraj	1	1	67
Uttar Pradesh - Faizabad	1	1	51
Uttar Pradesh - Gorakhpur	0	0	19
Uttar Pradesh - Deoria	0	1	10
Uttar Pradesh - Varansi	1	1	44
Uttarakhand - Dehradun	1	1	11
West Bengal - Darjiling	1	1	22
West Bengal - Jalpaiguri	1	1	33
West Bengal - Murshidabad	1	0	38
West Bengal - Birbhum	1	0	31
West Bengal - Barddhaman	1	0	63
West Bengal - Nadia	1	1	30
West Bengal - North 24 Parganas	1	1	26
West Bengal - Hugli	1	0	19
West Bengal - Bankura	1	1	6
West Bengal - Haora	1	0	15
West Bengal - Kolkata	1	1	36
West Bengal - South 24 Parganas	1	1	12
Jharkhand - Palamu	0	1	36
N			1147

- FCOLI = Faecal Coliform, and NIT = Nitrate-N + Nitrite-N, Obs. = Observations.
- Columns 1 and 2 indicate whether a district listed in the table experiences, on average, unsafe levels of faecal coliform and Nitrate-N + Nitrite-N, respectively. Districts experiencing unsafe levels of a pollutant are assigned a 1, and zero otherwise. Column 3 displays the number of observations for each district.

Table A.2: Analytical Sample Means of Key Variables

Correlation Matrix of Water Quality Variables					
District-level Means in rows and columns	FCOL	NIT	D.O.	B.O.D	pH
FCOL	1				
NIT	-0.0411	1			
D.O.	-0.2391	-0.0497	1		
B.O.D.	0.1958	0.3061	-0.667	1	
pH	-0.0386	0.0801	0.2494	-0.1206	1

Binary Indicators for Water Quality 1 = unsafe levels of district-mean reading	(1) FCOLI=1*	(2) NIT=1*	(3) D.O.=1*	(4) B.O.D.=1*	(5) pH=1*
Key Variables:					
Mean faecal Coliform (Millions MPN/100 mL) †	1.61	0.38	4.99	2.66	1.19
Mean Nitrate-N/Nitrite-N (mg/l)	1.20	2.77	0.64	1.58	0.92
Mean Biochemical Oxygen Demand (mg/l)	5.79	6.21	11.57	8.15	4.96
Mean Dissolved Oxygen (mg/l)	6.56	6.54	3.91	5.95	6.94
Mean pH	7.65	7.58	7.55	7.74	7.69
Reading Score	0.16	0.36	0.14	0.11	0.14
Maths Score	0.21	0.35	0.21	0.11	0.19
Writing Score	0.18	0.29	0.10	0.09	0.15
Age	9.49	9.59	9.47	9.55	9.48
Sex - Male	0.51	0.52	0.51	0.55	0.51
1[Majority Religious Group]	0.50	0.38	0.53	0.57	0.52
Anthropometry - height	127.15	126.41	126.87	127.16	127.01
Anthropometry - weight	25.38	25.23	25.44	25.54	25.34
1[HH per capita expenditure $\leq$ 25th ptile]	0.25	0.22	0.14	0.216	0.26
1[HH per capita expenditure $\leq$ 50th ptile]	0.49	0.47	0.40	0.44	0.51
1[HH per capita expenditure $\leq$ 75th ptile]	0.73	0.75	0.67	0.70	0.76
School Distance (Km)	1.66	1.55	1.69	1.66	1.57
School hours/week	29.38	28.12	29.28	30.98	30.27
Private Tuition hours/week	9.27	9.90	7.88	7.54	8.67
Books Uniform Cost	857.11	764.79	1002.63	983.04	822.01
Short-term Morbidity (days)	1.13	1.08	0.83	1.19	1.08
Water Purification**	0.11	0.08	0.09	0.08	0.09
Indoor Piped Drinking Water	0.15	0.13	0.15	0.16	0.12
Water Drinking Vessel***	0.79	0.84	0.73	0.78	0.70
Hand-wash****	0.72	0.69	0.75	0.77	0.72
Number of Observations	821	306	246	492	1111

† Mean faecal Coliform (MPN/100 ml), reported in millions.
* Pollution indicators. FCOL = 1, NIT = 1, D.O. = 1, B.O.D. = 1, pH = 1 mean unsafe levels of district-mean faecal coliform, Nitrtate-N + Nitrtite-N, Dissolved Oxygen, Biochemical Oxygen Demand respectively.
** Binary variable. 1 means household purifies water by boiling, filtering, aqua-guard, or chemicals.
*** Binary variable. 1 means household has water storage vessel.
****Binary variable. 1 means Members of the households always wash hands after defaecation.

Explanation for Table A.2

The first part of Table A.2 presents a correlation matrix for district-level mean water quality variables. Interestingly, certain pairs of district-level means, such as $FCOL$ and NIT, display a negative correlation. In Table A.2, the column means are derived from samples where water quality indicator readings fell below safety and/or recommended levels. For example, the variable *age* corresponds to the mean $\overline{age}|_{FCOL=1}$ in Column 1. It is observed that mean test scores are higher when $NIT = 1$ (Column 2) as compared to when $FCOL = 1$ (Column 2). Generally, the variable means show minimal variation across the columns. Notably, the rate of water purification in households is 0.75 when the biochemical oxygen demand exceeds its safe threshold, indicating that 75% of households treat their water before consumption. This percentage significantly surpasses that of households in the sample that purify their water when mean faecal coliform, mean Nitrate-N + Nitrite-N, and pH levels are not within safe limits.

Table A.3: Analytical Sample Means of Additional Control Variables

Variable	(1) $1[\overline{FCOLI} > limit]$ Districts	(2) $1[\overline{NIT} > limit]$ Districts	(3) River Districts	(4) All Districts
Short-term Morbidity (STM)				
1[Medical Insurance Coverage for last **STM**]	0.12	0.12	0.17	0.09
STM: Total cost***	47.12	46.08	58.80	49.78
STM: Days ill in last 30 days	1.65	1.73	1.70	1.53
STM: Days with fever in last 30 days	0.26	0.26	0.29	0.25
STM: Days with Cough in last 30 days	0.22	0.22	0.23	0.20
STM: Additional costs ♢	26.57	27.01	34.97	30.80
STM: Additional costs(2) ♢♢	2.75	1.99	2.21	2.69
Water Supply				
1[Water supply adequate]	0.95	0.98	0.98	0.96
Use of Technology in the HH				
1[HH respondent has mobile phone]	0.36	0.28	0.40	0.32
1[HH uses computer]	0.05	0.04	0.07	0.05
Schooling and Teaching-related				
If child gets free uniform (Yes = 1)	0.29	0.33	0.26	0.31
Years of Education completed: None	0.079	0.084	0.081	0.086
Years of Education completed: 1-4	0.73	0.73	0.73	0.73
Years of Education completed: primary or 5	0.11	0.11	0.12	0.12
Years of Education completed: 6-9	0.069	0.059	0.069	0.063
Scholarship Amount	76.98	75.60	76.63	75.76
School Fees (In thousand Rupees)	1.6	1.4	1.8	1.4
Child's teacher **(CT)**				
CT is fair to him/her (*Yes* = 1)	0.10	0.07	0.11	0.13
CT is biased (*Yes* = 1)	0.04	0.06	0.04	0.06
1[**CT** is local] (*Yes* = 1)	0.44	0.52	0.51	0.50
1[**CT** is female]	0.36	0.37	0.39	0.37
Parents attended PTA meeting (*Yes* = 1)	0.41	0.36	0.45	0.37
School Admission was difficult (*Yes* = 1)	0.28	0.32	0.26	0.31
Short-term Morbidity ♢♢♢	1.69	0 8	1.70	1.55
Urban = 1 and Rural = 0	0.36	0.31	0.44	0.36
Number of Observations	821	306	576	1147

***Mean Short-Term Morbidity Total cost for inpatient/outpatient (doctor and hospital).

• Column 1 shows means for the sample of districts with unsafe levels of faecal coliform, Column 2 shows means for the sample of districts with unsafe levels of Nitrate-N + Nitrite-N, Column 3 shows means for the sample of districts along rivers, and Column 4 shows means for the sample of all districts.

• FCOLI = Faecal Coliform, NIT = Nitrate-N + Nitrite-N, and HH = Household.

♢ Mean short-term Morbidity additional costs including medicines/tests/expenses which are not included in item (***).

♢♢ Mean short-term Morbidity travel expenses.

♢♢♢ District-wise average number of days spent disabled due to short-term morbidity.

Table A.4: PRATHAM's Assessment Framework

Assessment Framework	The assessment framework comprises three tests, each tailored to evaluate a distinct set of skills or knowledge areas. Unlike a uniform scoring system, these tests feature varying numbers of tasks, resulting in different maximum scores. Scores start at 0, representing no tasks completed, with the highest possible score corresponding to the total number of tasks within each test.
Test Outcomes	**Total points on the reading test score is 4**. The score is based on the child's ability to read a story. In the analytical sample, 12.45% of children cannot read the story (score 0), 11.88% can only recognise the letters (score 1), 17.96% can read some words (score 2), 16.27% can read paragraphs (score 3), and 41.44% can read the entire story (score 4). **The total writing test score is 2**: 27.44% cannot write at all (score 0), 29.14% write with one or two mistakes (score 1), and 43.42% produce error-free writing (score 2). **The total maths test score is 3**. It evaluates computational skills. 19.52% cannot recognise any numbers (score 0), 30.98% can recognise numbers (score 1), 24.47% can perform subtractions (score 2), and 25.04% can execute divisions correctly (score 3).

The tests were conducted by PRATHAM (2021), a non-governmental organisation in India.

Table A.5: Interaction between Indoor Piped Water Supply and Exposure to faecal Coliform above Safety Level

Test	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score	(7) Reading Score	(8) Maths Score	(9) Writing Score
Female	-0.0255	-0.0920	0.0306	-0.0175	-0.0866	0.0204	-0.0261	-0.0568	0.0778
	(0.0377)	(0.0495)	(0.0440)	(0.0577)	(0.0823)	(0.0682)	(0.0409)	(0.0598)	(0.0513)
(1) Household has	0.130	-0.328	0.894	0.0447	-0.267	0.818	0.216	-0.296	0.819
Indoor Piped Water Supply	(0.486)	(0.406)	(0.163)	(0.391)	(0.344)	(0.190)	(0.533)	(0.412)	(0.191)
$1[\overline{FCOLI} > limit]$	-0.244	-0.210	-0.189	-0.173	-0.150	-0.444	-0.482	-0.323	-0.0411
	(0.0837)	(0.105)	(0.148)	(0.160)	(0.173)	(0.192)	(0.122)	(0.142)	(0.184)
$(1) \times 1[\overline{FCOLI} > limit]$	-0.00651	0.389	-0.812	0.259	0.387	-0.803	-0.0373	0.546	-0.630
	(0.466)	(0.405)	(0.167)	(0.380)	(0.397)	(0.211)	(0.492)	(0.438)	(0.236)
$1[\overline{NIT} > limit]$	0.0529	-0.0347	-0.129	0.171	0.0441	-0.122	0.0254	-0.00812	-0.230
	(0.0732)	(0.0756)	(0.0835)	(0.231)	(0.129)	(0.215)	(0.0689)	(0.0886)	(0.107)
Observations	1147	1147	1147	576	576	576	738	738	738
Samples	All	All	All	River	River	River	Trib.	Trib.	Trib.

Robust standard errors clustered at district level in parentheses. FCOLI = Faecal Coliform and NIT = Nitrate-N + Nitrite-N

- The regression specifications corresponding the results in columns 1 to 9 include all explanatory variables used for results in Tables 3, 4, and 5 with additional controls for (1) whether respondent child receives scholarship for education, (2) year-round water availability (1=adequate, 0=inadequate), (3) drinking water storage vessel (1=the household has storage vessel, 0=none), (4) Whether the HH boils water to purify water (1=does, 0=does not), (5) frequency of washing hands after defaecation, (6) completed years of education, (7) Binary: Whether household has mobile phones, (8) Binary: Whether household has computer, (9) Short-term morbidity controls - the number of days the child was disabled in the last thirty days, the number of days the child showed certain symptoms like fever and coughing, and the amount of medical cost due to the short-term morbidity in the last thirty days, (10) school fees, whether the child gets free uniform (binary), costs of books, (11) Whether the household head considers the child's class teacher to be fair, parents' PTA participation (binary), child's teacher's gender, whether the child's admission to school was difficulty, frequency of child's teacher being absent at school. Lastly, district-level average short-term morbidity, state fixed effects, and survey month controls are also included to estimate each result.

Table A.6: Impact of Water Pollutants - Differences between Genders

All Districts	(1) Score Reading	(2) Score Maths	(3) Score Writing	(4) Score Reading	(5) Score Maths	(6) Score Writing
$1[\overline{FCOLI} > limit]$	-0.0726	-0.284	-0.112	-0.128	-0.0508	-0.110
	(0.104)	(0.176)	(0.116)	(0.106)	(0.119)	(0.159)
$1[\overline{NIT} > limit]$	-0.192	-0.174	-0.0387	-0.0833	0.0943	0.116
	(0.0867)	(0.196)	(0.0981)	(0.141)	(0.144)	(0.155)
$1[\overline{D.O.} < threshold]$	-0.114	0.00571	-0.0914	0.0379	-0.0609	-0.180
	(0.0983)	(0.155)	(0.100)	(0.109)	(0.137)	(0.118)
Mean pH	-0.102	-0.190	-0.0373	-0.199	-0.526	-0.242
	(0.123)	(0.245)	(0.0806)	(0.150)	(0.172)	(0.146)
N	592	592	592	555	555	555
Gender	Male	Male	Male	Female	Female	Female
Overall R^2	0.30	0.27	0.27	0.19	0.26	0.29
Districts near Rivers	(7) Score Reading	(8) Score Maths	(9) Score Writing	(10) Score Reading	(11) Score Maths	(12) Score Writing
$1[\overline{FCOLI} > limit]$	0.0329	-0.183	-0.464	-0.534	-0.582	-0.369
	(0.164)	(0.165)	(0.216)	(0.105)	(0.153)	(0.182)
$1[\overline{NIT} > limit]$	0.0214	0.151	-0.0944	-0.231	-0.0863	0.153
	(0.149)	(0.113)	(0.203)	(0.237)	(0.162)	(0.202)
$1[\overline{D.O.} < threshold]$	-0.171	-0.0856	0.0712	0.281	0.155	-0.159
	(0.187)	(0.200)	(0.223)	(0.174)	(0.185)	(0.211)
Mean pH	-0.120	-0.118	0.130	0.190	-0.149	0.0942
	(0.242)	(0.293)	(0.210)	(0.189)	(0.246)	(0.164)
N	285	285	285	291	291	291
Gender	Male	Male	Male	Female	Female	Female
Overall R^2	0.35	0.36	0.27	0.31	0.34	0.38

Robust standard errors clustered at district level in parentheses.
Pollutants: FCOLI = faecal coliform, NIT = Nitrate-N + Nitrite-N, D.O. = Dissolved Oxygen

- **Explanatory variables not reported** : Numerical variables such as Age, Height, Weight, "hours spent at school per week", "hours spend doing homework per week", "hours spent being tutored per week", "distance from school to home", "number of days the child spent disabled because of short-term morbidity in the last 30 days". Binary Variables such as Sex, "Rupees spent on books and uniform $>$ Rs. 500", "household consumption per capita $\leq$ 25th percentile", "household consumption $\leq$ 50th percentile", "household consumption $\leq$ 75th percentile", "1 = water storage vessel available at home", "1 = water is purified at home though some mode of filtration or boiling", "1 = household members always wash hands after defaecation".

Explanation for Table A.6

We examine the impact of faecal coliform and Nitrate-N + Nitrite-N on boys versus girls in Table A.6. Most columns in this table do not present estimates that are statistically significant from zero. The comparison of the effect of $1[\overline{FCOLI} > limit]$ between Column 9 and Column 12 reveals a less than 0.095 standard deviation greater estimated effect on boys in writing tests, indicating that the effect of poor water quality is not necessarily uniform across genders. The analytical sample means in Table A.7 show that boys do not consistently outperform girls in tests across districts with unsafe pollutant levels. However, in districts with safe levels of pollutants, boys generally score higher. This disparity may be attributed to the fact that areas with safe faecal coliform levels are often rural, where girls may face more discrimination in educational investment and greater barriers to education.

Furthermore, we investigate whether girls in the sample received disproportionately lower investment in their education and if poor water quality and the adoption of water pollution mitigation technology affected them differently compared to boys. In Tables A.8 and A.9, we include interaction terms to explore such possibilities. The estimated effects of interaction terms between being female and having faecal coliform levels above the safety level, the cost of books and uniforms incurred by the household, and whether the household has an indoor pump are examined in Table A.8. Although the interaction effects of being female and the cost of books and uniforms in 1000 Rupees are statistically significant in Columns 7, 10, and 11, they cannot be fully interpreted due to the non-significant main effect of being female in these columns. We also explore interactions between being female and variables related to water availability and water purification in Table A.9. However, most estimated coefficients of these interaction terms are not statistically significant. It is possible that girls receive disproportionately less attention and investment from households regarding their education and are more affected by changes in water availability and exposure to water pollution, but our analyses in Tables A.8 and A.9 do not find sufficient statistical evidence to confirm this.

Table A.7: Comparison of Mean Male and Female Test Scores by District-level Prevalence of Water Pollution

		$1[\overline{FCOLI} > limit]$	$1[\overline{NIT} > limit]$	$0[\overline{FCOLI} \leq limit]$	$0[\overline{NIT} \leq limit]$
Sex					
Male	Reading	0.155 (0.929)	0.373 (0.816)	0.09 (0.891)	0.051 (0.938)
Male	Maths	0.234 (1.02)	0.432 (0.984)	0.256 (0.945)	0.171 (0.999)
Male	Writing	0.147 (0.999)	0.281 (0.945)	0.133 (0.997)	0.092 (0.945)
Sex					
Female	Reading	0.177 (0.929)	0.346 (0.828)	0.025 (0.948)	0.59 (0.962)
Female	Maths	0.194 (1.007)	0.265 (0.943)	0.042 (0.964)	0.112 (1.014)
Female	Writing	0.212 (0.993)	0.302 (0.910)	0.103 (1.01)	0.139 (1.026)

- Reading, Writing, and Maths Test Scores have been Z-scored for the entire sample. Standard Deviations in parentheses.
- FCOLI = Faecal Coliform, NIT = Nitrate-N + Nitrite-N.
- Columns 1 and 2 show test score means for districts with unsafe levels of faecal coliform and Nitrate-N + Nitrite-N, respectively, while Columns 3 and 4 show test score means for districts within safe levels of these pollutants.

Table A.8: Differential Effect of Water Pollution on Girls

	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
Female	-0.00831	-0.124	0.0511	0.0716	-0.0269	-0.0163
	(0.0684)	(0.0987)	(0.0810)	(0.0844)	(0.0640)	(0.0758)
(1) $1[\overline{FCOLI} > limit]$	-0.231	-0.222	-0.197	-0.107	-0.0804	-0.547
	(0.0907)	(0.139)	(0.177)	(0.194)	(0.201)	(0.239)
Female × (1)	-0.0223	0.0465	-0.0283	-0.0919	-0.0658	0.0457
	(0.0806)	(0.128)	(0.109)	(0.112)	(0.101)	(0.103)
$1[\overline{NIT} > limit]$	0.0498	-0.0353	-0.133	0.0948	0.00750	-0.109
	(0.0744)	(0.0751)	(0.0872)	(0.260)	(0.131)	(0.228)
Observations	1147	1147	1147	576	576	576
Sample	All	All	All	River	River	River

	(7) Reading Score	(8) Maths Score	(9) Writing Score	(10) Reading Score	(11) Maths Score	(12) Writing Score
Female	0.0274	-0.0458	0.0100	0.0631	0.0112	0.0343
	(0.0517)	(0.0497)	(0.0497)	(0.0928)	(0.102)	(0.0747)
(2) Cost of Books, Uniform	0.103	0.0665	0.0163	0.0940	0.0799	-0.0134
in 1000 Rupees.	(0.0291)	(0.0377)	(0.0363)	(0.0494)	(0.0543)	(0.0360)
Female × (2)	-0.0630	-0.0555	0.0257	-0.0806	-0.109	-0.0138
	(0.0293)	(0.0355)	(0.0330)	(0.0466)	(0.0490)	(0.0356)
$1[\overline{FCOLI} > limit]$	-0.243	-0.199	-0.211	-0.169	-0.133	-0.526
	(0.0833)	(0.101)	(0.155)	(0.169)	(0.168)	(0.223)
$1[\overline{NIT} > limit]$	0.0415	-0.0426	-0.130	0.0699	-0.0295	-0.117
	(0.0745)	(0.0756)	(0.0870)	(0.267)	(0.144)	(0.231)
Observations	1147	1147	1147	576	576	576
Sample	All	All	All	River	River	River

	(13) Reading Score	(14) Maths Score	(15) Writing Score	(16) Reading Score	(17) Maths Score	(18) Writing Score
Female	-0.0317	-0.0907	0.0247	-0.0193	-0.0838	-0.00166
	(0.0401)	(0.0479)	(0.0442)	(0.0650)	(0.0836)	(0.0626)
(3) HH has indoor piped water	0.0939	0.0292	0.134	0.252	0.0666	0.0534
	(0.115)	(0.0872)	(0.136)	(0.125)	(0.129)	(0.149)
Female × (3)	0.0593	-0.00682	0.0434	0.0222	-0.00904	0.143
	(0.0930)	(0.103)	(0.165)	(0.119)	(0.169)	(0.200)
$1[\overline{FCOLI} > limit]$	-0.244	-0.199	-0.213	-0.149	-0.113	-0.526
	(0.0821)	(0.101)	(0.155)	(0.154)	(0.163)	(0.214)
$1[\overline{NIT} > limit]$	0.0549	-0.0348	-0.128	0.160	0.0238	-0.0689
	(0.0730)	(0.0755)	(0.0850)	(0.232)	(0.122)	(0.214)
Observations	1147	1147	1147	576	576	576
Sample	All	All	All	River	River	River

- Robust standard errors clustered at district level in parentheses. FCOLI = Faecal Coliform and NIT = Nitrate-N + Nitrite-N
- The regression specifications corresponding the results in columns 1 to 18 include all explanatory variables used for results in Tables 3, 4, and 5 with additional controls for (1) whether respondent child receives scholarship for education, (2) year-round water availability (1=adequate, 0=inadequate), (3) drinking water storage vessel (1=the household has storage vessel, 0=none), (4) HH boils water to purify water (1=does, 0=does not), (5) frequency of washing hands after defaecation, (6) completed years of education, (7) Binary: Whether household has mobile phones, (8) Binary: whether household has computer, (9) short-term morbidity controls - the number of days the child was disabled in the last thirty days, the number of days the child showed certain symptoms like fever and coughing, and the amount of medical cost due to the short-term morbidity in the last thirty days, (10) school fees, whether the child gets free uniform (binary), costs of books, (11) Whether the household head considers the child's class teacher to be fair, parents' PTA participation (binary), child's teacher's gender, whether the child's admission to school was hard, frequency of child's teacher being absent at school. Lastly, district-level average short-term morbidity, state fixed effects, and survey month controls are also included to estimate each result.

Table A.9: Differential Effect of Water Pollution on Girls (continued...)

	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
Female	0.0114	-0.141	-0.181	0.331	-0.493	-0.225
	(0.183)	(0.303)	(0.361)	(0.337)	(0.346)	(0.278)
(1) Water availability normal	-0.165	-0.0181	-0.0279	0.0272	0.124	-0.0852
the whole year = 1	(0.157)	(0.149)	(0.187)	(0.276)	(0.292)	(0.285)
Female × (1)	-0.0366	0.0511	0.219	-0.343	0.417	0.252
	(0.190)	(0.308)	(0.360)	(0.344)	(0.333)	(0.257)
$1[\overline{FCOLI} > limit]$	-0.242	-0.199	-0.212	-0.155	-0.115	-0.524
	(0.0834)	(0.100)	(0.157)	(0.164)	(0.164)	(0.224)
Nitrate/Nitrite unsafe levels	0.0496	-0.0350	-0.132	0.0968	0.0147	-0.109
	(0.0746)	(0.0749)	(0.0875)	(0.262)	(0.130)	(0.227)
Observations	1147	1147	1147	576	576	576
Sample	All	All	All	River	River	River

	(7) Reading Score	(8) Maths Score	(9) Writing Score	(10) Reading Score	(11) Maths Score	(12) Writing Score
Female	-0.107	-0.189	0.0986	0.00506	0.240	0.368
	(0.0705)	(0.164)	(0.209)	(0.211)	(0.425)	(0.265)
(2) Water availability normal	0.0909	0.106	-0.0727	-0.0132	-0.331	-0.362
during summer	(0.0873)	(0.158)	(0.211)	(0.236)	(0.417)	(0.304)
Female × (2)	-0.0630	-0.0555	0.0257	-0.0806	-0.109	-0.0138
	(0.0293)	(0.0355)	(0.0330)	(0.0466)	(0.0490)	(0.0356)
$1[\overline{FCOLI} > limit]$	-0.228	-0.187	-0.192	-0.118	-0.0948	-0.515
	(0.0840)	(0.103)	(0.157)	(0.159)	(0.163)	(0.215)
Nitrate/Nitrite unsafe levels	0.0487	-0.0356	-0.137	0.0725	0.00707	-0.114
	(0.0747)	(0.0757)	(0.0849)	(0.259)	(0.121)	(0.226)
Observations	1147	1147	1147	576	576	576
Sample	All	All	All	River	River	River

	(13) Reading Score	(14) Maths Score	(15) Writing Score	(16) Reading Score	(17) Maths Score	(18) Writing Score
Female	-0.107	-0.189	0.0986	0.00506	0.240	0.368
	(0.0705)	(0.164)	(0.209)	(0.211)	(0.425)	(0.265)
(3) HH purifies water	-0.0478	-0.0304	0.274	0.000347	0.461	0.296
before drinking	(0.111)	(0.157)	(0.194)	(0.217)	(0.302)	(0.346)
Female × (3)	0.0593	-0.00682	0.0434	0.0222	-0.00904	0.143
	(0.0930)	(0.103)	(0.165)	(0.119)	(0.169)	(0.200)
$1[\overline{FCOLI} > limit]$	-0.228	-0.187	-0.192	-0.118	-0.0948	-0.515
	(0.0840)	(0.103)	(0.157)	(0.159)	(0.163)	(0.215)
$1[\overline{NIT} > limit]$	0.0487	-0.0356	-0.137	0.0725	0.00707	-0.114
	(0.0747)	(0.0757)	(0.0849)	(0.259)	(0.121)	(0.226)
Observations	1143	1143	1143	573	573	573
Sample	All	All	All	River	River	River

- Robust standard errors clustered at district level in parentheses. FCOLI = Faecal Coliform and NIT = Nitrate-N + Nitrite-N
- The regression specifications corresponding the results in columns 1 to 18 include all explanatory variables used for results in Tables 3, 4, and 5 with additional controls for (1) whether respondent child receives scholarship for education, (2) year-round water availability (1=adequate, 0=inadequate), (3) drinking water storage vessel (1=the household has storage vessel, 0=none), (4) Whether the HH boils water to purify water (1=does, 0=does not), (5) frequency of washing hands after defaecation, (6) completed years of education, (7) Binary: Whether household has mobile phones, (8) Binary: Whether household has computer, (9) Short-term morbidity controls - the number of days the child was disabled in the last thirty days, the number of days the child showed certain symptoms like fever and coughing, and the amount of medical cost due to the short-term morbidity in the last thirty days, (10) school fees, whether the child gets free uniform (binary), costs of books, (11) Whether the household head considers the child's class teacher to be fair, parents' PTA participation (binary), child's teacher's gender, whether the child's admission to school was difficulty, frequency of child's teacher being absent at school. Lastly, district-level average short-term morbidity, state fixed effects, and survey month controls are also included to estimate each result.

Table A.10: Differences in River Pollution Effect across States

Test	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score	(7) Reading Score	(8) Maths Score	(9) Writing Score
$1[\overline{FCOLI} > limit]$	-0.235	-0.203	-0.287	-0.0905	-0.0519	-0.448	0.192	0.180	-0.293
	(0.130)	(0.0820)	(0.184)	(0.175)	(0.164)	(0.0880)	(0.133)	(0.283)	(0.163)
$1[\overline{NIT} > limit]$	-0.0767	-0.131	0.219	–	–	–	-0.0343	0.0556	-0.0547
	(0.173)	(0.119)	(0.164)	–	–	–	(0.0734)	(0.166)	(0.0810)
$1[\overline{D.O.} < threshold]$	0.0336	-0.0674	-0.249	-0.485	-0.487	0.129	0.105	0.0888	-0.0112
	(0.186)	(0.153)	(0.197)	(0.118)	(0.127)	(0.0722)	(0.0998)	(0.167)	(0.106)
Mean pH	0.0122	-0.399	-0.0383	1.472	1.023	0.707	-0.125	-0.573	0.355
	(0.170)	(0.135)	(0.230)	(1.076)	(1.014)	(0.751)	(0.268)	(0.329)	(0.248)
N	422	422	422	347	347	347	367	367	367
States	UP	UP	UP	WB	WB	WB	BJ	BJ	BJ

Robust standard errors clustered at district level in parentheses. FCOLI = Faecal Coliform and NIT = Nitrate-N + Nitrite-N

- UP = Uttar Pradesh, BJ = Bihar and Jharkhand, and WB = West Bengal.
- **The results in columns 1 to 9 are estimated by including the following control variables in the regression equation** : Numerical variables such as Age, Sex, Height, Weight, "hours spent at school per week", "hours spend doing homework per week", "hours spent being tutored per week", "distance from school to home", "number of days the child spent disabled because of short-term morbidity in the last 30 days". Binary Variables such as Sex, "Rupees spent on books and uniform $>$ Rs. 500", "household consumption per capita $\leq$ 25th percentile", "household consumption $\leq$ 50th percentile", "household consumption $\leq$ 75th percentile", "1 = water storage vessel available at home", "1 = water is purified at home though some mode of filtration or boiling", "1 = household members always wash hands after defaecation".

Table A.11: Robustness Check with Additional Education-related and Short-term Morbidity-related Controls

	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
$1[\overline{FCOLI} > limit]$	-0.0435	-0.196	-0.113	-0.297	-0.0372	-0.356
	(0.0671)	(0.141)	(0.0839)	(0.130)	(0.121)	(0.182)
$1[\overline{NIT} > limit]$	-0.164	-0.0538	-0.00910	0.114	0.0259	0.0590
	(0.0792)	(0.171)	(0.0754)	(0.0952)	(0.0916)	(0.177)
$1[\overline{D.O.} < threshold]$	-0.0319	0.0713	-0.0661	-0.00994	-0.156	-0.0722
	(0.0971)	(0.162)	(0.101)	(0.136)	(0.115)	(0.205)
Mean pH	0.0276	0.217	-0.237	-0.0533	-0.0313	0.175
	(0.0988)	(0.164)	(0.129)	(0.202)	(0.0932)	(0.191)
School distance	-0.0162	-0.0218	0.0199	0.0105	-0.00142	0.0180
	(0.0121)	(0.0176)	(0.0101)	(0.0154)	(0.0132)	(0.0191)
School hrs/week	-0.00590	-0.0138	-0.00482	-0.00288	-0.00991	-0.0192
	(0.00383)	(0.00447)	(0.00385)	(0.00451)	(0.00484)	(0.00567)
Homework hrs/week	0.0259	0.0277	0.0272	0.0276	0.0290	0.0311
	(0.00506)	(0.00750)	(0.00577)	(0.00684)	(0.00443)	(0.00616)
Pvt. Tuition hrs/week	0.0108	0.0187	0.0214	0.0249	0.0251	0.0329
	(0.00590)	(0.00893)	(0.00877)	(0.0112)	(0.00751)	(0.0119)
Cost Books, uniform	0.323	0.269	0.222	0.176	0.326	0.245
	(0.0570)	(0.0796)	(0.0539)	(0.0949)	(0.0554)	(0.0889)
STM days disabled†	0.00610	-0.0155	-0.00430	0.0126	-0.0272	-0.0258
	(0.0131)	(0.0163)	(0.0144)	(0.0246)	(0.00937)	(0.0210)
Indoor Piped Water	0.109	-0.0764	0.0510	-0.202	0.0267	-0.0852
	(0.0831)	(0.0960)	(0.0710)	(0.108)	(0.0842)	(0.0884)
1 to 4 years of Edu.	0.646	0.737	0.577	0.662	0.486	0.571
	(0.117)	(0.194)	(0.0888)	(0.0898)	(0.121)	(0.157)
N	1147	576	1147	576	1147	576
Sample	All	River	All	River	All	River
Overall R^2	0.30	0.27	0.27	0.19	0.26	0.29

- Robust standard errors clustered at district level in parentheses.
- Pollutants: FCOLI = faecal coliform, NIT = Nitrate-N + Nitrite-N, D.O. = Dissolved Oxygen.
  †STM = short-term morbidity.
- **Explanatory variables not reported** :Numerical variables such as Age, Sex, Height, Weight, "household consumption per capita $\leq$ 25th percentile", "household consumption $\leq$ 50th percentile","household consumption $\leq$ 75th percentile", "1 = water storage vessel available at home", "1 = water is purified at home though some mode of filtration or boiling", "1 = household members always wash hands after defaecation".
- **Additional Controls for Robustness checks**: Private Tuition child receives hours/week, Short-term morbidity expenditure, 1 = Water availability is normal/adequate, Completed Years of schooling, 1 = Primary respondent of household owns mobile, 1 = Primary respondent of household uses a computer, Short-term morbidity - total cost, short-term morbidity - number of days ill in the last 30 days, Number of days with fever in the last 30 days, Number of days with cough in the last 30 days, Cost of treatment - travelling to health centre, cost of treatment - tests, medicines, miscellaneous. Descriptive Statistics of Teacher Quality variables are available in Description of these variables can be found in Table A.3. .

Explanation for Table A.11

Compared to the effects estimated in Tables 3 and 5, the impact of $1[\overline{FCOLI} > limit]$ on reading and writing test scores is approximately 0.005 standard deviations lower in Table A.11. Moreover, Column 1 in Table A.11 shows that the estimated effect of $1[\overline{NIT} > limit]$ is statistically significant for the full sample, whereas the effect of $1[\overline{FCOLI} > limit]$ on maths and writing test scores is not statistically significant.

Table A.12: Robustness Check with Teaching quality Controls

	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
$1[\overline{FCOLI} > limit]$	-0.0459	-0.150	-0.132	-0.294	-0.0382	-0.359
	(0.0864)	(0.174)	(0.0820)	(0.132)	(0.146)	(0.210)
$1[\overline{NIT} > limit]$	-0.161	-0.0611	-0.00779	0.0772	0.0259	0.0393
	(0.0817)	(0.157)	(0.0803)	(0.0664)	(0.102)	(0.156)
$1[\overline{D.O.} < threshold]$	0.0130	0.145	-0.0150	0.131	-0.115	0.0826
	(0.0881)	(0.163)	(0.0938)	(0.108)	(0.121)	(0.197)
Mean pH	0.0819	0.276	-0.227	-0.0393	-0.0350	0.224
	(0.0945)	(0.153)	(0.107)	(0.118)	(0.122)	(0.201)
T Fair	-0.146	-0.153	-0.163	-0.203	0.00382	0.0135
	(0.0863)	(0.112)	(0.0963)	(0.131)	(0.0886)	(0.156)
PTA Participation	0.0713	0.0471	0.138	0.277	0.0936	0.233
	(0.0773)	(0.0812)	(0.0687)	(0.0743)	(0.0802)	(0.0881)
T Biased	-0.0996	-0.184	0.0839	-0.0448	0.00904	0.438
	(0.117)	(0.213)	(0.1000)	(0.147)	(0.127)	(0.182)
Local T	0.152	0.212	0.175	0.211	0.174	0.167
	(0.0489)	(0.0855)	(0.0689)	(0.0838)	(0.0837)	(0.115)
Female T	0.0490	-0.0568	0.0438	0.0328	0.0421	-0.134
	(0.0434)	(0.0513)	(0.0634)	(0.0838)	(0.0738)	(0.0711)
T Attendance Regular	0.0824	0.170	0.0201	0.116	0.0494	0.101
	(0.0583)	(0.0917)	(0.0751)	(0.0826)	(0.0791)	(0.0784)
S Admission difficult	-0.0590	-0.134	0.101	0.0412	0.0649	-0.0115
	(0.0908)	(0.112)	(0.0966)	(0.161)	(0.0892)	(0.128)
N	1147	576	1147	576	1147	576
Sample	All	River	All	River	All	River

- Robust standard errors clustered at district level in parentheses.
- T = teacher. S = School. PTA = Parent-Teacher Association. FCOLI = faecal coliform, NIT = Nitrate-N + Nitrite-N, D.O. = Dissolved Oxygen
- The regression specifications corresponding the results in columns 1 to 6 include all explanatory variables used for results in Table A.11

Table A.13: Mixed-effects Specifications - Random Intercepts

	(1) Reading Score	(2) Reading Score	(3) Reading Score	(4) Reading Score	(5) Reading Score	(6) Reading Score
$1[\overline{FCOLI} > limit]$	-0.109	-0.582	-0.234	-0.0290	-0.288	0.0170
	(0.0777)	(0.308)	(0.112)	(0.135)	(0.161)	(0.114)
$1[\overline{NIT} > limit]$	-0.129	-0.0563	-0.0650	-0.104	-0.00507	-0.0621
	(0.0805)	(0.196)	(0.0974)	(0.115)	(0.146)	(0.124)
N	1147	206	532	769	576	738
Sample	All	Lake	Ganges	GW	River	Trib.
	(7) Maths Score	(8) Maths Score	(9) Maths Score	(10) Maths Score	(11) Maths Score	(12) Maths Score
$1[\overline{FCOLI} > limit]$	-0.145	-0.669	-0.322	0.106	-0.192	-0.0420
	(0.0874)	(0.267)	(0.119)	(0.197)	(0.180)	(0.121)
$1[\overline{NIT} > limit]$	-0.0444	0.112	0.0868	-0.000282	0.163	-0.166
	(0.0925)	(0.178)	(0.104)	(0.177)	(0.164)	(0.131)
N	1147	206	532	769	576	738
Sample	All	Lake	Ganges	GW	River	Trib.
	(13) Writing Score	(14) Writing Score	(15) Writing Score	(16) Writing Score	(17) Writing Score	(18) Writing Score
$1[\overline{FCOLI} > limit]$	-0.157	-0.341	-0.355	-0.00710	-0.378	-0.103
	(0.0944)	(0.278)	(0.150)	(0.111)	(0.175)	(0.120)
$1[\overline{NIT} > limit]$	0.0878	-0.0870	0.119	0.0242	0.112	0.0907
	(0.102)	(0.186)	(0.134)	(0.0945)	(0.160)	(0.128)
N	1147	206	532	769	576	738
Sample	All	Lake	Ganges	GW	River	Trib.

- Robust standard errors clustered at district level in parentheses.
- FCOLI = Faecal Coliform, NIT = Nitrate-N + Nitrite-N, GW = groundwater.
- The regression specifications corresponding the results in columns 1 to 18 include all explanatory variables used for results in Tables 3, 4, and 5.

Table A.14: Baseline Model Estimated with Random Intercepts at Two Levels, District and Village

Test	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
$1[\overline{FCOLI} > limit]$	-0.0412	-0.161	-0.142	-0.281	-0.0839	-0.365
	(0.0788)	(0.148)	(0.0865)	(0.133)	(0.0989)	(0.173)
$1[\overline{NIT} > limit]$	-0.134	-0.0196	-0.00644	0.110	0.102	0.0785
	(0.0777)	(0.135)	(0.0862)	(0.118)	(0.106)	(0.158)
$1[\overline{D.O.} < threshold]$	-0.0448	0.0353	-0.0536	0.0204	-0.144	-0.0254
	(0.0754)	(0.145)	(0.0823)	(0.130)	(0.0935)	(0.173)
Mean pH	0.0618	0.247	-0.198	-0.0956	-0.0712	0.0944
	(0.104)	(0.192)	(0.114)	(0.161)	(0.131)	(0.223)
N	1147	576	1147	576	1147	576
Districts	All	River	All	River	All	River

Robust standard errors clustered at district level in parentheses.
"Uttarakhand" is the reference State to the State dummy variables.

- **The results in columns 1 to 6 are estimated by including all the control variables used for Table A.16 results except Mean District-level Short-term Morbidity.**

Explanation for Table A.14

Table A.14 presents findings from a two-level random-intercept model used for additional robustness checks. This model accommodates the hierarchical structure of the data by recognising villages and/or neighbourhoods as the primary levels within which the surveyed children are 'nested.' By adopting this approach, we can estimate the effects of $1[\overline{FCOLI} > limit]$ and $1[\overline{NIT} > limit]$ on the dependent variable, considering potential intra-group correlations within each village or neighbourhood. The results shown in Table A.14 indicate that the estimated effects of exceeding safe levels of faecal coliform and nitrate-nitrite are consistent and statistically significant in the two-level random-intercept model.

Table A.15: Baseline Regression - Random Intercepts at Three Levels (District, Village, and Household)

Test	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
$1[\overline{FCOLI} > limit]$	-0.0452	-0.163	-0.131	-0.275	-0.0823	-0.361
	(0.0800)	(0.147)	(0.0887)	(0.135)	(0.100)	(0.170)
$1[\overline{NIT} > limit]$	-0.134	-0.0187	-0.0167	0.108	0.0904	0.0702
	(0.0787)	(0.134)	(0.0885)	(0.120)	(0.107)	(0.156)
$1[\overline{D.O.} < threshold]$	-0.0314	0.0389	-0.0548	0.0210	-0.131	-0.00979
	(0.0767)	(0.144)	(0.0846)	(0.132)	(0.0951)	(0.170)
Mean pH	0.0520	0.241	-0.187	-0.0915	-0.0771	0.103
	(0.105)	(0.190)	(0.117)	(0.164)	(0.132)	(0.218)
N	1147	576	1147	576	1147	576
Districts	All	River	All	River	All	River

Robust standard errors clustered at district level in parentheses. DO = Dissolved Oxygen.
"Uttarakhand" is the reference State to the State dummy variables.

- **The results in columns 1 to 6 are estimated by including all the control variables used for table A.16 results except Mean District-level Short-term Morbidity.**

Explanation for Table A.15

Table A.15 extends the multilevel analysis presented in Table A.14 by adding households as an additional level, creating a three-level random-intercept model. This more granular approach allows for the consideration of variation both within and between households, villages, and neighbourhoods, providing a comprehensive view of the data's nested structure. The results in Table A.15 offer insight into the impact of water pollutants, with specific attention to faecal coliform and nitrate-nitrite levels that surpass safe thresholds. The estimated effects remain statistically robust even when the household level is included.

Table A.16: Robustness Check with District-level Morbidity as Control

Test	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
$1[\overline{FCOLI} > limit]$	-0.0120	-0.147	-0.106	-0.295	0.0413	-0.303
	(0.0832)	(0.172)	(0.0813)	(0.128)	(0.130)	(0.191)
$1[\overline{NIT} > limit]$	-0.154	-0.0554	0.00218	0.0854	0.0347	0.0443
	(0.0774)	(0.159)	(0.0824)	(0.0774)	(0.0896)	(0.159)
$1[\overline{D.O.} < threshold]$	-0.0548	0.0341	-0.0750	0.0295	-0.216	-0.0759
	(0.0948)	(0.159)	(0.0920)	(0.116)	(0.117)	(0.209)
Mean pH	0.0422	0.195	-0.249	-0.0887	-0.0561	0.202
	(0.0882)	(0.141)	(0.114)	(0.145)	(0.0985)	(0.167)
Mean Morbidity	-0.00502	0.00481	-0.00852	-0.00318	-0.0710	-0.0874
	(0.0155)	(0.0298)	(0.0181)	(0.0305)	(0.0175)	(0.0323)
N	1147	576	1147	576	1147	576
Districts	All	River	All	River	All	River

Robust standard errors clustered at district level in parentheses. DO = Dissolved Oxygen
T = teacher. S = School. PTA = Parent-Teacher Association

- **The results in columns 1 to 6 are estimated by including all the control variables used for Table A.12 results.**

Explanation of Table A.16

The channel through which water pollution affects educational outcomes is the deterioration of the child's health, primarily followed by a decrease in cognitive abilities. We only control for short-term morbidity and do not have any measure of long-term morbidity. As a control for the district-wide morbidity level, we create a measure of the district-average short-term morbidity of the children within a district. As a control variable, it should account for the average effect of district-level short-term morbidity caused by water pollution. Controlling for the channel of short-term morbidity may leave the secondary channel of a decrease in cognitive abilities through long-term morbidity or recurring short-term morbidity open. We observe that short-term morbidity, when included in the model, weakens the effect of $1[\overline{FCOLI} > limit]$ on writing test scores in districts where water was monitored (Column 6 in Table A.16, compared to Column 6 in Table A.11). However, the effect of $1[\overline{FCOLI} > limit]$ on reading scores in districts along rivers and that of $1[\overline{NIT} > limit]$ on reading scores in the all-district sample remain statistically robust.

Table A.17: Robustness Check with State Fixed Effects

Test	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
$1[\overline{FCOLI} > limit]$	-0.212	-0.202	-0.171	-0.186	-0.254	-0.545
	(0.0911)	(0.189)	(0.0966)	(0.161)	(0.147)	(0.245)
$1[\overline{NIT} > limit]$	-0.0774	-0.0146	0.0345	0.0973	0.126	0.152
	(0.0721)	(0.138)	(0.0909)	(0.0905)	(0.0853)	(0.108)
$1[\overline{D.O.} < threshold]$	-0.0366	-0.00498	-0.0703	0.00795	-0.132	-0.166
	(0.0799)	(0.138)	(0.0987)	(0.119)	(0.108)	(0.138)
Mean pH	0.0914	0.206	-0.223	-0.115	0.134	0.234
	(0.123)	(0.143)	(0.163)	(0.161)	(0.149)	(0.142)
Uttar Pradesh	0.358	0.215	0.739	0.633	0.484	0.307
	(0.0989)	(0.156)	(0.144)	(0.172)	(0.136)	(0.171)
Bihar	0.116	0.0396	0.809	0.862	0.0904	-0.0496
	(0.162)	(0.252)	(0.162)	(0.175)	(0.150)	(0.241)
West Bengal	0.555	0.168	1.109	0.814	0.719	0.666
	(0.179)	(0.232)	(0.172)	(0.194)	(0.162)	(0.182)
Jharkhand	0.00586	-	0.611	-	0.424	-
	(0.238)	-	(0.227)	-	(0.201)	-
N	1147	576	1147	576	1147	576
Districts	All	River	All	River	All	River

Robust standard errors clustered at district level in parentheses. DO = Dissolved Oxygen
"Uttarakhand" is the reference State to the State dummy variables.

- **The results in Columns 1 to 6 are estimated by including all the control variables used for Table A.16 results except Mean District-level Short-term Morbidity.**

Explanation for Table A.17

If state-specific policies in pollution control and education provision are connected through the channel of quality governance, then the pollution treatment effects would be underestimated. So, we add state fixed effects to our model and estimate the results in Table A.17. Table A.17 presents the change in the coefficient estimates of unsafe levels of faecal coliform and Nitrate-N + Nitrite-N after the inclusion of state-fixed effects. We can see that the effect of $1[\overline{NIT} > limit]$ in column 1 of Table A.17 - compared to column 1 in Table A.16 - is indistinguishable from zero. On the other hand, the estimated effect of $1[\overline{FCOLI} > limit]$ remains statistically significant for writing (Columns 3 and 6), reading (Column 1), and math (Column 5). The state dummy for Jharkhand is not identified because the only district in Jharkhand in our analytical sample, Palamu, is not situated by a river. Overall, we find the math score to be less responsive to pollution. According to Ashraf (2020) and Babu (2012), and due to resource constraints faced by rural and/or public schools and poorer sections of the urban population, teaching math compared to other subjects is more difficult. This difficulty likely results in low variations in the math test score and therefore sees little effect of factors like river pollution.

Table A.18: Checking for Seasonality
State_ID × District Mean Morbidity × Survey Month

	(1) Reading Score	(2) Reading Score	(3) Reading Score	(4) Reading Score	(5) Reading Score	(6) Reading Score
$1[\overline{FCOLI} > limit]$	-0.303	-0.0974	0.0433	-0.302	0.00431	-0.722
	(0.0831)	(0.410)	(0.201)	(0.161)	(0.198)	(0.113)
$1[\overline{NIT} > limit]$	-0.0542	-0.346	0.404	0.0162	0.379	-0.172
	(0.0731)	(0.200)	(0.283)	(0.0756)	(0.317)	(0.0777)
N	1147	206	532	769	576	738
Sample	All	Lake	Ganges	GW	River	Trib.

	(7) Maths Score	(8) Maths Score	(9) Maths Score	(10) Maths Score	(11) Maths Score	(12) Maths Score
$1[\overline{FCOLI} > limit]$	-0.246	-0.132	-0.230	-0.156	-0.235	-0.319
	(0.106)	(0.274)	(0.116)	(0.156)	(0.129)	(0.116)
$1[\overline{NIT} > limit]$	0.0115	-0.181	0.245	0.0943	0.185	-0.0665
	(0.0788)	(0.134)	(0.532)	(0.0761)	(0.138)	(0.115)
N	1147	206	532	769	576	738
Sample	All	Lake	Ganges	GW	River	Trib.

	(13) Writing Score	(14) Writing Score	(15) Writing Score	(16) Writing Score	(17) Writing Score	(18) Writing Score
$1[\overline{FCOLI} > limit]$	-0.160	-0.181	-0.437	-0.0540	-0.436	0.0596
	(0.143)	(0.349)	(0.205)	(0.115)	(0.203)	(0.162)
$1[\overline{NIT} > limit]$	0.0698	0.101	0.0529	0.0531	-0.00564	0.164
	(0.110)	(0.186)	(0.258)	(0.0845)	(0.254)	(0.137)
N	1147	206	532	769	576	738
Sample	All	Lake	Ganges	GW	River	Trib.

- Robust standard errors clustered at district level in parentheses.
- The regression specifications corresponding the results in columns 1 to 18 include all explanatory variables used for results in Tables 3, 4, and 5 with additional controls for (1) whether respondent child receives scholarship for education, (2) year-round water availability (1=adequate, 0=inadequate), (3) drinking water storage vessel (1=the household has storage vessel, 0=none), (4) Whether the HH boils water to purify water (1=does, 0=does not), (5) frequency of washing hands after defaecation, (6) completed years of education, (7) Binary: Whether household has mobile phones, (8) Binary: Whether household has computer, (9) Short-term morbidity controls - the number of days the child was disabled in the last thirty days, the number of days the child showed certain symptoms like fever and coughing, and the amount of medical cost due to the short-term morbidity in the last thirty days, (10) school fees, whether the child gets free uniform (binary), costs of books, (11) Whether the household head considers the child's class teacher to be fair, parents' PTA participation (binary), child's teacher's gender, whether the child's admission to school was difficulty, frequency of child's teacher being absent at school.

Explanation for Table A.18

As the data used in this paper is cross-sectional, there is little opportunity to detect and control for seasonality for multiple years. Table A.18 shows how the effect of $1[\overline{FCOLI} > limit]$ changes in the presence of extensive controls for seasonality. Therefore, we include interaction terms - $State\_ID \times Disctrict\_Mea\_Morbidity \times Survey\_Month$ - in the empirical model and present the results in Table A.18. These interaction terms control for survey-month specific variations in district-level average child short-term morbidity 'in the last thirty days from the date of the survey month' by states. Faecal coliform effects for reading and Maths in the first column (full sample) of Table A.18 are statistically significant after including these interaction terms. These interaction terms are viable controls under the assumption that within a state, district-level average short-term morbidity in different months remain unchanged over 2011 and 2012 - the two years when the last wave of the survey took place - and that in the months when the survey was not conducted - July, August, and September - seasonal variation in district-level average short-term morbidity does not exceed that of the previous and subsequent months.

Table A.19: Robustness checks: Proxying for Air Pollution using PM2.5 in 2012

	(1) Reading Score	(2) Reading Score	(3) Reading Score	(4) Reading Score	(5) Reading Score	(6) Reading Score
$1[\overline{FCOLI} > limit]$	-0.245	-1.088	-0.0874	-0.265	-0.160	-0.448
	(0.0868)	(0.805)	(0.157)	(0.164)	(0.187)	(0.129)
$1[\overline{NIT} > limit]$	0.0579	0.307	0.0410	-0.0132	0.124	0.0218
	(0.0833)	(0.262)	(0.271)	(0.0775)	(0.265)	(0.0721)
PM2.5 in 2012	-0.00141	-0.0144	0.0119	0.00686	-0.00764	0.00748
	(0.00371)	(0.0193)	(0.01610)	(0.00768)	(0.00502)	(0.00830)
N	1147	206	532	769	576	738
Sample	All	Lake	Ganges	GW	River	Trib.
	(7) Maths Score	(8) Maths Score	(9) Maths Score	(10) Maths Score	(11) Maths Score	(12) Maths Score
$1[\overline{FCOLI} > limit]$	-0.209	0.769	-0.0521	-0.236	-0.122	-0.320
	(0.105)	(1.125)	(0.160)	(0.168)	(0.179)	(0.148)
$1[\overline{NIT} > limit]$	0.00927	-0.0162	-0.0194	-0.0437	0.0474	0.000753
	(0.0828)	(0.275)	(0.117)	(0.117)	(0.135)	(0.0892)
PM2.5 in 2012	-0.00772	0.0297	0.00138	-0.0121	-0.0114	-0.00720
	(0.00326)	(0.0274)	(0.00673)	(0.00775)	(0.00471)	(0.00612)
N	1147	206	532	769	576	738
Sample	All	Lake	Ganges	GW	River	Trib.
	(13) Writing Score	(14) Writing Score	(15) Writing Score	(16) Writing Score	(17) Writing Score	(18) Writing Score
$1[\overline{FCOLI} > limit]$	-0.213	-0.937	-0.472	-0.00802	-0.525	-0.0339
	(0.158)	(1.316)	(0.229)	(0.118)	(0.228)	(0.185)
$1[\overline{NIT} > limit]$	-0.126	-0.279	-0.156	-0.0586	-0.102	-0.241
	(0.101)	(0.379)	(0.207)	(0.0705)	(0.228)	(0.112)
PM2.5 in 2012	-0.00134	0.00350	0.0130	0.000578	-0.00293	0.000297
	(0.00408)	(0.0307)	(0.01732)	(0.00556)	(0.00534)	(0.00801)
N	1147	206	532	769	576	738
Sample	All	Lake	Ganges	GW	River	Trib.

- Robust standard errors clustered at district level in parentheses.
- The regression specifications corresponding the results in columns 1 to 18 include all explanatory variables used for results in Tables 3, 4, and 5 with additional controls for (1) whether respondent child receives scholarship for education, (2) year-round water availability (1=adequate, 0=inadequate), (3) drinking water storage vessel (1=the household has storage vessel, 0=none), (4) Whether the HH boils water to purify water (1=does, 0=does not), (5) frequency of washing hands after defaecation, (6) completed years of education, (7) Binary: Whether household has mobile phones, (8) Binary: Whether household has computer, (9) Short-term morbidity controls - the number of days the child was disabled in the last thirty days, the number of days the child showed certain symptoms like fever and coughing, and the amount of medical cost due to the short-term morbidity in the last thirty days, (10) school fees, whether the child gets free uniform (binary), costs of books, (11) Whether the household head considers the child's class teacher to be fair, parents' PTA participation (binary), child's teacher's gender, whether the child's admission to school was difficulty, frequency of child's teacher being absent at school. Lastly, district-level average short-term morbidity, state fixed effects, and survey month controls are also included to estimate each result.

Explanation for Table A.19

Table A.19 provides results illustrating the effects of unsafe levels of faecal coliform and Nitrate-N + Nitrite-N, as well as PM2.5 in 2012. Even after the inclusion of PM2.5 as a control variable, the impact of unsafe levels of faecal coliform on reading scores remains statistically significant for the full sample (Column 1, Table A.19) and the sample of districts along tributaries (Column 6, Table A.19). Moreover, the effect of unsafe levels of faecal coliform was also found to be statistically significant on writing scores (Columns 15 and 17, Table A.19) and on maths scores (Columns 7 and 12). PM2.5 itself exhibited a statistically significant negative effect only on maths test scores in Columns 7 and 11.

Table A.20: The Effect of District-level Mean faecal Coliform Instrumented by Mean faecal Coliform in the Immediate Upstream District

All Districts	(1) Reading Score	(2) Maths Score	(3) Writing Score	(4) Reading Score	(5) Maths Score	(6) Writing Score
Model	RE	RE	RE	RE-IV	RE-IV	RE-IV
Mean FCOLI	-0.0991	-0.0722	0.0308	-0.321	0.0445	0.0855
	(0.0505)	(0.0377)	(0.0256)	(0.147)	(0.0976)	(0.0791)
Mean NIT	-0.384	-0.276	-0.368	-0.352	-0.293	-0.376
	(0.277)	(0.221)	(0.138)	(0.390)	(0.180)	(0.135)
N	871	871	871	871	871	871

River Districts	(7) Reading Score	(8) Maths Score	(9) Writing Score	(10) Reading Score	(11) Maths Score	(12) Writing Score
Model	RE	RE	RE	RE-IV	RE-IV	RE-IV
Mean FCOLI	-0.00365	-0.000807	-0.000521	-0.000751	-0.0000480	0.000206
	(0.000735)	(0.000862)	(0.000904)	(0.000199)	(0.000224)	(0.000284)
Mean NIT	-1.681	-0.549	-0.483	-1.602	-0.604	-0.460
	(0.269)	(0.316)	(0.317)	(0.233)	(0.266)	(0.276)
N	460	460	460	460	460	460

Tributary Districts	(13) Reading Score	(14) Maths Score	(15) Writing Score	(16) Reading Score	(17) Maths Score	(18) Writing Score
Model	RE	RE	RE	RE-IV	RE-IV	RE-IV
Mean FCOLI	-0.716	-0.819	-0.0919	-0.717	-0.819	-0.0919
	(0.362)	(0.446)	(0.402)	(0.362)	(0.446)	(0.402)
Mean NIT	0.249	0.668	-0.296	0.249	0.668	-0.296
	(0.444)	(0.429)	(0.441)	(0.444)	(0.429)	(0.441)
N	567	567	567	567	567	567

- Robust standard errors clustered at district level in parentheses. MeanFCOL = district-average faecal coliform MPN/100 ml, in millions. MeanNIT = district-average Nitrate-N + Nitrite-N mg/l. The results in columns labeled "RE-IV" utilize the district-average faecal coliform amount, which is instrumented by the average level of faecal coliform from its upstream neighbouring district.
- MeanFCOL$>$2500 MPN per 100 ml is the safety limit for faecal coliform. Mean NITRATE- N+ NITRITE-N are measured in miligrams per litre of water. The regression specifications corresponding the results in columns 1 to 18 include all explanatory variables used for results in Tables 3, 4, and 5 with additional controls for (1) whether respondent child receives scholarship for education, (2) year-round water availability (1=adequate, 0=inadequate), (3) drinking water storage vessel (1=the household has storage vessel, 0=none), (4) Whether the HH boils water to purify water (1=does, 0=does not), (5) frequency of washing hands after defaecation, (6) child's years of schooling, (7) binary: Whether household has mobile phones, (8) binary: Whether household has computer, (9) Short-term morbidity controls - the number of days the child was disabled in the last thirty days, the number of days the child showed certain symptoms like fever and coughing, and the amount of medical cost due to the short-term morbidity in the last thirty days, (10) school fees, whether the child gets free uniform (binary), costs of books, (11) Whether the household head considers the child's class teacher to be fair, (12) whether parents participate in PTA meetings (binary), (13) child's teacher's gender, (14) binary: whether the child's admission to school was difficulty, (15) frequency of child's teacher being absent at school.

Explanation for Table A.20

Pollution in upstream areas can often have significant consequences for downstream environments and communities, but the factors influencing this pollution upstream are reasonably independent from the factors influencing negative consequences downstream. Later in Section 4, we discuss some results where downstream district pollution is instrumented with upstream district pollution[27].

We introduce an additional model to tackle the concern regarding the extent to which the impact of water quality was influenced by pollution originating from upstream districts. In this model, we employ district-level pollution as an instrumental variable, using the pollution levels of districts upstream and those sharing borders as counterparts. A comparable strategy is adopted by Do et al. (2018) to untangle localized unobserved variables from measurements of river water pollution. It is worth noting that pollution originating in upstream regions can negatively impact downstream environments and communities. The factors influencing this upstream pollution are generally independent of the observed and unobserved factors that contribute to pollution downstream. Therefore, for this analysis, we update our initial model as follows

$$Z_{ik} = \alpha_{ik} + Mean\widehat{FCOLI}_k + \widetilde{\mathbf{W}}'\Theta + \mathbf{X}'\Gamma + \chi_k + \varepsilon_{ik} \tag{3}$$

$$MeanFCOLI_k = \beta_1 + \widetilde{\mathbf{W}}'\Psi + \mathbf{X}'\Delta + upstream\_MeanFCOLI_k + \omega_k + u_{ik} \tag{4}$$

With the assumption that $E(upstream_MeanFCOLI|\omega_k) = 0$, $\widetilde{\mathbf{W}}$ is the vector of water quality indicators except faecal coliform. Testing the validity of instruments becomes more complex with binary endogenous variables. Standard over-identification tests and tests for endogeneity might not apply in a straightforward way. Therefore, we use the district-level mean

[27] For this instrumentation scheme, we trace the course of the river and identify one neighbouring upstream district for each downstream district. We only select the upstream district that is also adjacent or sharing administrative borders. This process is straightforward because, in the Ganges basin, most rivers and tributaries flow from northwest to southeast. The sample used in this particular analysis excludes some districts whose upstream counterpart was not included in IHDS.

faecal coliform measures, $MeanFCOLI_k$ and $upstream_MeanFCOLI_k$, instead of binary measures. Unlike $1[\overline{FCOLI} > limit]$, $Mean\widehat{FCOLI}_k$ cannot be interpreted in a way that makes economic sense. As an additional robustness check, this exercise serves to show if faecal coliform instrumented by its upstream measure still affects test scores when it is disentangled from the district-level unobserved factors through instrumentation. For this development, we do lose some observations because not every district has an adjacent counterpart district along the same river that has also been included in the IHDS survey by Desai and Vanneman (2015). For this part, we use random-effects generalised 2SLS methods to estimate the instrumented model.

For accuracy, we instrument the district's faecal coliform level only with that of a border-sharing upstream district. For this exercise, we retain fewer observations compared to our primary analysis. We did not find data for upstream and border-sharing districts of 2 districts in Bihar, 2 districts in West Bengal, 1 district in Uttarakhand, and 3 districts in Uttar Pradesh. This choice is made considering that pollution generated by more distant districts tends to decay to some extent, potentially weakening the anticipated effect on downstream pollution levels. This portion of the analysis only discusses results from the instrumentation of district-average level of faecal coliform and not district-average level of Nitrate-N + Nitrite-N due to little variation between upstream and downstream levels of Nitrate-N + Nitrite-N. Overall, we have seen little effect of Nitrate-N + Nitrite-N on test scores; therefore, an additional analysis with the upstream district-average level of Nitrate-N + Nitrite-N as an instrument has been skipped in this section.

The outcomes of this instrumental variable (IV) analysis are outlined in Table A.20. We present the results from both the random-effects model and the random-effects model with instrumentation side by side for easy comparison. The results in columns labelled RE-IV are estimated using generalised 2SLS random-effects methods. Results in Columns 1 to 6 are based on the all-district sample, Columns 7 to 12 for districts along rivers, and Columns 12 to 18 for districts along tributaries. Applying upstream faecal coliform measure as an instrument reveals a statistically significant impact of the district-average faecal coliform level on reading scores in three samples: all districts, river-adjacent districts, and tributary-adjacent districts.

Additionally, we observe that instrumented *MeanFCOLI* has some weak effect on maths test scores in the all-district sample and the ’tributaries’ sample. However, we do not observe any statistically significant effect of instrumented *MeanFCOLI* on Writing Score, which might result from using smaller samples where the treatment *MeanFCOLI* varies only at the district level.