Nijmegen School of Management
Department of Economics and Business Economics
Master's Thesis Economics (MAN-MTHEC)

When Water Turns Toxic: The Impact of River Pollution on Child Nutritional Status in India

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Nijmegen, 5 July 2024

Program: Master's Program in Economics
Specialisation: International Economics & Development
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Abstract

This thesis examines the relationship between river water pollution and child nutritional status in India by combining two rounds of the Indian Human Development Survey with river water quality data from GEMStat. The sample consists of 2,508 children who were aged 0-5 years old in 2005 and were reinterviewed in 2012, matched to district-level yearly average river water pollution values. Lags of water pollution are included in the analysis to account for the delayed effect on health. A multi-way fixed effect regression model is used to estimate the relationship over time. The results indicate that a 10% increase in river water pollution levels from the previous year decreases the nutritional status of an average child in the sample by approximately 0.4%. Further analysis shows that an average child exposed to poor district-level river water quality in the previous year has a 10.5% lower nutritional status than a child from a district with excellent river water quality. Water pollution affects boys and children from households with lower-educated heads more strongly than girls and children from higher-educated households. Urban children are more affected by current levels of pollution, whereas rural children experience a stronger effect from pollution in the previous year.

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1 Introduction

Despite global efforts, the progress on reaching the Sustainable Development Goal of safe drinking water for all by 2030 remains behind. In 2022, 2.2 billion people still lacked safe drinking water services free of contamination (United Nations, 2023). As climate change is exacerbating water scarcity around the world, people may have to rely increasingly on polluted water sources. Globally, poor water quality is associated with 80% of diseases and 50% of deaths among children (Lin et al., 2022). Exposure to pollution during childhood is related to long-term consequences for health and economic outcomes (Currie et al., 2014).

This thesis examines the relationship between river water pollution and the nutritional status of children in India. Young children are particularly vulnerable to pollution because their bodies and immune systems are developing rapidly (Drisse et al., 2010). Diarrhoea is major cause of nutritional deficits in children, and can be traced back to poor water quality (Das et al., 2014). Childhood exposure to chemicals such as those found in wastewater are also linked to childhood and adult diseases, neurodevelopmental issues, and infant mortality (Wigle et al., 2008).

Reducing water pollution may therefore lead to increases in child nutritional status, improving children's lives. Child health also predicts long-term outcomes such as educational attainment, health, and social status (Case et al., 2005). Addressing the problem can also be useful for policy development from an economic standpoint, as a healthier population can increase national income through higher labour productivity, educational attainment, and savings (Bloom & Canning, 2009). Improving these conditions in India could further enhance children's welfare.

Therefore, the following research question will be answered: *To what extent does river water pollution exposure affect child nutritional status in India?*

Yearly district-level river water pollution data from GEMStat is linked to household- and individual-level panel data from two rounds (2005 and 2012) of the Indian Human Development Survey (IHDS). The combination of these data sources has not been used before. The relationship between river water pollution and nutritional status in India is examined for 2,508 children who were 0-5 years old in the first survey round and reinterviewed in the second survey round, using a multi-way fixed-effect regression model. The models include values of water pollution from previous years to examine the delayed impact of pollution on child nutritional status.

The results suggest that a 10% increase in river water pollution levels from the previous year decreases the nutritional status of an average child in the sample by approximately 0.4%. Furthermore, an average child exposed to poor district-level river water quality in the previous year has a 10.5% lower nutritional status than a child from a district with excellent river water quality. Heterogeneity analyses show that boys are disproportionately affected by river water pollution, as well as children from households with lower-educated heads. Urban children are more affected by current levels of pollution, and rural children experience a stronger effect from pollution in the previous year.

As country-wide survey-based longitudinal studies on water pollution and child health in India are scarce, this thesis aims to provide a valuable contribution to the literature. Previous research has largely focused on the effects of air pollution on child health (Schwartz, 2004), where the direct impact on health is quite obvious. The pathway from river water pollution to child exposure is less clear. Research using panel data to examine the effects of water pollution on child nutritional status are especially scarce, and lagged values of water pollution to capture the delayed effect on health are rarely taken into account. A study closely related to the present study is Brainerd and Menon (2014), which investigates the effect of state-level averages of fertilizers in water on infant and child health. By considering district-level water pollution levels using a general measure for water pollution, this study can provide a more nuanced understanding of the relationship between water pollution and child nutritional status.

2 Conceptual framework

2.1 River pollution in India

Water pollution is the contamination of rivers, lakes, oceans, and groundwater. It poses a major threat to public health, especially in developing countries such as India. Many Indian cities and towns originated and are still located along the riverbanks (Singh, 2018). Rivers are used for agricultural and industrial practices as well as bathing, washing clothes and even drinking (Hamner et al., 2006). In the last few decades, India has been plagued by high levels of surface water and groundwater pollution. The three major sources of water pollution are industrial waste, sewage, and agricultural runoff (Rajaram & Das, 2008). In India, urban and industrial wastewater often goes untreated before it is disposed of, contaminating surface water and groundwater (Aulakh et al., 2009). Increased pesticide and fertilizer use after the Green Revolution that started in the 1960s also led to higher levels of water pollution (Singh, 2000). In an effort to reduce river water pollution the government has taken several initiatives. For example, the first Ganga Action Plan was launched in 1985, but it failed to meet its objectives by 2000 (Srinivas et al., 2020). They also formed the Central Pollution Control Board, which found that 70% of its monitored rivers were still polluted in 2015 (Press Information Bureau Delhi, 2023). Greenstone and Hanna (2014) concluded that Indian air pollution regulations have reduced air pollution, but no measurable effect of water regulations was found.

2.2 Children and malnutrition

According to Drisse et al. (2010), children are more vulnerable to pollution than adults and they respond differently as their bodies are still developing. Their risk of exposure to pollutants is higher than adults since they spend more time outdoors, coming into contact with contaminants while playing. Children more often bring their hands to their mouths, further increasing the risk of exposure as they can accidentally ingest soil or water. In the womb, they are indirectly exposed to pollution through their mothers.

Very few studies have investigated the relationship between river water pollution and children's nutritional status using national panel surveys. Brainerd and Menon (2014) did, and found a modest effect of agrochemical water pollution on nutritional status. Case studies have found evidence of a relationship between pollution of local drinking water sources and children's nutritional status (Garg et al., 2018; Minamoto et al., 2005). Studies on air pollution have also found negative effects on children's nutritional status (Goyal & Canning, 2018; Kim et al., 2016). Aside from pollution, nutritional status can be influenced by a combination of many different factors such as food security, dietary intake, access to healthcare, sanitation, illness, income, and education (Garrett & Ruel, 1999).

Water pollution has negative health effects and can affect children's nutritional status through several channels which are explained in the following sections. Figure 1 shows a conceptual model illustrating the relationship between river water pollution and the nutritional status of children.

2.3 Exposure pathways

2.3.1 Drinking water contamination

One major way in which children can be exposed to river water pollution is through the consumption of contaminated drinking water. Fawell and Nieuwenhuijsen (2003) describe how drinking water can be contaminated by pathogens, naturally occurring chemicals such as arsenic and fluoride, industrial waste containing metals and solvents, and agrochemicals such as pesticides and fertilizers. All of these pollutants have been associated with health issues (Azizullah et al., 2011). Pollution becomes an issue for drinking water especially when the treatment of surface water is insufficient (Fawell & Nieuwenhuijsen, 2003). For example, several studies have found empirical evidence that pesticide pollution in surface water contaminates drinking water sources, and dangerous levels can persist even after the water has been treated (Chau et al., 2015; Kruawal et al., 2005; Toan et al., 2013). Others point out that contaminated water obtained for municipal water supplies can lead to the contamination of piped drinking water when it is improperly treated (Brick et al., 2004).

Untreated groundwater is the main source of drinking water in most of India, often extracted by hand pumps and tube wells (Jain et al., 2010). According to Winter et al. (1998), river water and groundwater influence each other in a process called groundwater-surface water interaction. The authors explain that river water and groundwater are hydraulically connected, allowing pollutants to easily seep into the groundwater. While certain pollutants are filtered out of the water as it passes through the soil, persistent pollutants such as heavy metals, solvents and agrochemicals can contaminate large areas of groundwater (Schwarzenbach et al., 1983). A number of studies have concluded that polluted Indian rivers contaminate groundwater that is extracted for drinking purposes (Dhakyanaika & Kumara, 2010; Pranavam et al., 2011; Somasundaram et al., 1993). Especially arsenic contamination is a major cause of concern in India. Rivers deposit sediments carrying naturally occurring and industrially discharged arsenic, which contaminates the groundwater, resulting in a wide array of arsenic-related diseases among the population (Chakraborti et al., 2017; Chowdhury et al., 2000; Shaji et al., 2021). Arsenic in drinking water from tube wells was found to have a negative impact on children's nutritional status in rural Bangladesh (Minamoto et al., 2005). Drinking water sources such as wells can also be contaminated with fecal bacteria from rivers that end up in groundwater, especially in case extreme weather events like heavy rainfall and floodings, increasing the risk of diarrheal disease (Gowrisankar et al., 2017; Page et al., 2012).

Exposure to polluted drinking water can thus result in many adverse child health outcomes through disease. Heavy metal contamination has been associated with malnutrition-related diseases and even with a reduction in immunity gained from vaccinations, exacerbating children's vulnerability to pollutants (Zheng et al., 2023). Diarrheal diseases are often fatal to infants through dehydration, and 80-90% of them are caused by environmental pollutants (Creel, 2002). When diarrhea is not fatal, children can subsequently suffer from negative health effects such as malnutrition and neurodevelopmental delays (Manetu et al., 2021). Motarjemi et al. (1993) explain how polluted drinking water can also contaminate weaning food given to infants, leading to diarrhea and malnutrition.

2.3.2 Agricultural consequences

Surface water and groundwater are two major sources of irrigation water in India (Roy & Shah, 2002). When polluted river water is used for this purpose, it leaches into the soil and can degrade soil and crop quality by contaminating it with toxins and heavy metals (Prabu, 2009; Singh et al., 2021; Weldegebriel et al., 2012). In India, multiple studies concluded that soil and crops irrigated by water from nearby rivers contained heavy metal concentrations above the permissible limits (Saha et al., 2014; Singh et al., 2021). Consuming food with heavy metals can deprive the body of essential nutrients, which can lead to many health issues that result in malnutrition (Iyengar & Nair, 2000). In children, consumption of heavy metal-contaminated food is associated with neurological damage, cancer, respiratory issues and impaired growth (Al

Osman et al., 2019). Setia et al. (2020) found empirical evidence that the Sutlej River in India contaminates nearby groundwater sources used for irrigation purposes with heavy metals, and that the cancer rates are higher in areas around the river.

Crops can also be affected in the absence of irrigation, when they are grown on the banks of polluted rivers, as the water infiltrates and contaminates the soil (Bahemuka & Mubofu, 1999).

2.3.3 Other pathways

In addition, using polluted rivers for bathing or washing clothes has been associated with diseases and diarrhea (Garg et al., 2018; Halder & Islam, 2015; Hanif et al., 2020). Hamner et al. (2006) also found that bathing, brushing teeth, washing clothes and utensils with water from the river Ganges in India was highly associated with a number of water-borne diseases. Children can also be exposed to pollutants such as heavy metals when playing outdoors, for example by ingesting contaminated soil by bringing hands or toys to the mouth (Drisse et al., 2010; Mielke et al., 1999; Shezi et al., 2022). Another way in which children can be exposed is through the consumption of contaminated fish from polluted rivers. Many studies have found that fish from rivers in India are heavily contaminated with pollutants such as heavy metals, which can lead to adverse health effects (Maurya et al., 2019; Siddiqui et al., 2019; Singh et al., 2014).

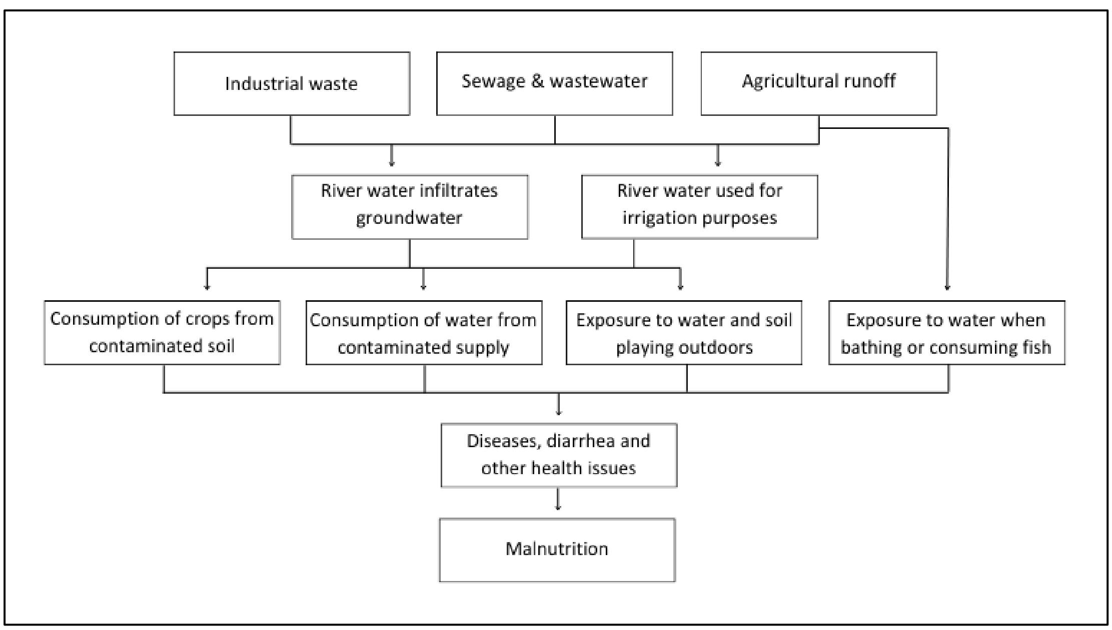

FIGURE 1: CONCEPTUAL MODEL OF THE PROPOSED RELATIONSHIP AND ITS CHANNELS

3 Data and methods

3.1 Data source and sample

Panel data on individuals and households is obtained from the Indian Human Development Survey (IHDS), which is available at the Inter-university Consortium for Political and Social Research (ICPSR) (Desai et al., 2019). The survey was conducted in two rounds, in 2005 and 2012. Over 42,152 households across India participated, with 85% of them being reinterviewed after the first survey round (University of Maryland, 2022a). The survey covers a large number of individual- and household-related topics. The data has been used in a number of studies focused on children's outcomes in India (Choudhuri & Desai, 2021; Lei et al., 2020; Li et al., 2018; Liu et al., 2015; Vikram & Vanneman, 2020).

Water pollution data is obtained from GEMStat. Several prior studies on surface water pollution have made use of the database (Brainerd & Menon, 2014; Ridzuan, 2021; Russ et al., 2022; Sigman, 2002, 2014). This study will focus on rivers as river monitoring stations are the main source of Indian water quality data at GEMStat (GEMS/Water Data Centre, 2023). Also, rivers are a severely polluted in India, and policy interventions have given much attention to the issue (Greenstone & Hanna, 2014). In the IHDS, geographic information is provided at the district-level, not the village, due to ethical clearance guidelines (University of Maryland, 2022b). For this reason, district-level water pollution data will be assigned to the children. The unfiltered water dataset contains 468 water stations located in 250 districts within 26 states. See Appendix A for a map of all available water stations. There are 290 water stations with water quality values in both 2005 and 2012. Water data from 2005 and 2012 is used, as well as one-year lags, as there may be a delayed effect of exposure on health outcomes. The annual average pollution level of the combined data from all stations in a particular district is calculated, resulting in one pollution value per district per year.

The IHDS dataset includes 19,065 children aged 0-5 in the 2005 survey round, who were reinterviewed in the 2012 survey round. Children who were interviewed in 2004 and/or 2011 are excluded as it is impossible they experienced the effect of water pollution levels in the subsequent years. In the models with lagged variables, children born after the lagged year are excluded as they would not have been (directly) exposed to the pollution in that year. After merging the IHDS data with the district-level yearly average pollution levels and removing children with missing values for the outcome variable, the final dataset is comprised of 2,508 children located in 89 districts within 13 states. Appendix B contains a map that visualizes these locations.

3.2 Variables and measures

Below, the included variables are described. See Tables C1, C2, C3, and C4 in Appendix C for summary statistics of the variables used in the analyses and their state-wise distributions.

The variable Weight-for-age z-score (WAZ) as included in the IHDS is used as the measure of child nutritional status. This measure has been used in other studies examining the impact of water quality on health (Brainerd & Menon, 2014; Null et al., 2018). One study used the same variable from the IHDS to estimate the relationship between household water treatment and children's nutritional status (Li et al., 2018). The World Health Organization provides information on weight-for-age z-scores and their computation (WHO, 2008). The variable refers to children's weight for their age and gender standardized against a reference population, ranging from -6 to 6. The z-scores are computed with WHO *Child growth standards* as the international reference, and they measure the distance in standard deviations (SD) between a child's weight and the median weight of a child of the same age and gender from the reference population. When a score is -2 SD away from the median a child is classified as underweight, and -3 SD means the child is severely underweight.

The water quality parameter Biochemical Oxygen Demand (BOD) is used as a measure of water pollution. It is defined as the amount of oxygen micro-organisms need to remove organic matter in the water (European Environment Agency, 2023). Sigman (2002) also uses BOD data from GEMstat to evaluate pollution levels in rivers. The author describes BOD as a widely used measure of water pollution and implies that the standardization of its measurement ensures consistent results across states and districts. It is also one of the water quality parameters most often reported in GEMStat data from Indian monitoring stations, enabling the analysis of a large sample size. A limitation of using this parameter is that it does not provide details about the specific pollutants responsible for the changes in BOD, which would make it difficult to identify the sources of health issues. The variable is measured in mg/L and is log-transformed into a normally distributed variable. For an extension of the main analysis, the variable is converted into a categorical variable with the categories 'Excellent' (lower than 1 mg/L), 'Good' (between 1 and 2 mg/L), 'Fair' (between 2 and 6 mg/L), and 'Poor' (higher than 6 mg/L), following the water quality criteria of the Meadowlands Environmental Research Institute (n.d.).

Table 1 provides an overview with descriptions of all control variables, obtained from the IHDS. The analysis controls for water- and sanitation-related household-level variables such as water source, water purification and soap use as this could determine drinking water quality and exposure to disease, thereby affecting child health outcomes. As nutritional status is related to food security, the analysis controls for the number of meals consumed in the household. Household income and size is controlled for as these variables are associated with malnutrition due to poorer resource availability (Pelto et al., 1991). Lastly, education of the household head is taken into account as higher education levels can improve child nutritional status through proper nutrition practices (Parmenter et al., 2000; Titus & Adetokunbo, 2007).

TABLE 1: CONTROL VARIABLE DESCRIPTIONS

Variable	**Description**
Water Source	The usual main household drinking water source. Categories are Piped (piped water, public supply), Improved (tube well, hand pump, covered well, rainwater), and Unimproved (open well, river/canal/stream, pond, tanker truck, bottled, and others), following the definitions of the WHO (n.d.-a)
Water Purification	Whether the household treats or purifies drinking water by boiling, filtering, using chemicals or Aquagard. Categories are Never, Rarely, Usually, and Always.
Soap Use	Whether soap is used to wash hands. A dummy variable equal to 1 if soap is used, 0 if not.
Meals	Number of meals consumed per day per person in the household.
Age	Age of the child in months.
Household Income	Annual household income, log-transformed
Household Size	Number of persons in the household.
Education Head	Education level of the head of the household. Categories are None, Primary, Middle, Secondary, High Secondary and Bachelor's.

3.3 Empirical strategy and regression model

In order to investigate how water pollution affects child nutritional status over time, a fixed-effects linear regression model is developed to capture the nutritional status of a child *i* in household *h* located in district *d* and state *s* in year *t*. The baseline model is specified as follows:

$$(1)\quad WAZ_{i,h,d,s,t} = \beta_1(ln)BOD_{d,s,t} + \beta_2(ln)BOD_{d,s,t-1} + \beta_3 Controls_{i,h,t} + \alpha_i + \delta_{s,t} + \epsilon_{i,h,d,s,t}$$

Where WAZ measures children's weight-for-age z-scores in 2005 and 2012. The variable BOD measures the log-transformed annual average of station-level Biochemical Oxygen Demand per district in years 2005 and 2012. To account for the possible delayed effect of pollution exposure on nutritional status, one-year lags of BOD are included for the years 2004 and 2011. The vector *Controls* reflects the individual- and household-specific control variables.

α_i denotes individual fixed effects which account for any characteristics specific to the child that are unobserved and time-invariant, such as genetic makeup. δ_{st} denotes state-by-year fixed effects which account for state-level shocks that are applicable to all children living in a state in a given year.

The standard errors are clustered at multiple levels due to the hierarchical nature of the data. First, they are clustered at the household level to account for autocorrelation as observations within the same household are likely to be correlated due to similarities between household members. Second, children and households observed in the same district and year may have similar experiences, such as similar policies, economic conditions and environmental factors. To account for spatial correlation across all households within the same district-year combinations, the standard errors are clustered at the district-by-year level.

This study possibly suffers from endogeneity issues. There can be a number of unobserved factors affecting both river water pollution and malnutrition. For example, poor communities can be more susceptible to both water pollution and malnutrition and district-level economic development can affect both variables. Moreover, households with children with poor nutritional statuses may suffer from poverty and thus live in polluted areas due to lower housing costs; this could mean nutritional status determines whether households reside near polluted rivers. A useful solution to endogeneity issues could be Instrumental Variable Analysis, which was considered but deemed unfeasible due to data limitations. This study tries to deal with these problems at least partially by including fixed effects, performing robustness checks, clustering standard errors and controlling for factors such as income, meal intake, and household education. State-level GDP is also an important variable to consider but could not be included due to data limitations. One way in which the risk of measurement error was reduced was by removing water quality measurements flagged as poor quality.

4 Results

4.1 Main results

Table 2 presents the estimates of the relationship between river water pollution (BOD) and the weight-for-age z-score (WAZ). Column (1) shows the results of the regression of WAZ on BOD. Column (2) shows the estimates for the model where WAZ is regressed on both BOD and lagged BOD.

According to the results in Column (1), a 10% increase in current BOD decreases the WAZ by 0.026 standard deviations (SD). The result is statistically significant at the 1% level. This finding is in line with the expectation that river water pollution negatively affects nutritional status. To put this effect size into context, the change in the WAZ of an average child in the sample can be calculated. The mean WAZ of a 3-year-old boy in the 2005 sample is -1.88. A 10% increase in BOD would mean the child's weight decreases by approximately 35 grams, from 11.441 kg to 11.406 kg[1], which is a 0.3% decrease in body weight. This effect size is quite small, but perhaps over time, such small effects of pollution can accumulate and have profound effects on the body. Brainerd and Menon (2014) find a similar but slightly lower effect, with a 10% increase in the average level of agrichemicals in water decreasing the WAZ by 0.014 SD. All controls are not statistically significant except for Age, with a 1-month increase in Age being

[1] Calculated using World Health Organization instructions on the computation of weight-for-age z-scores (WHO, 2008), and tables with reference data of boys' weight-for-age z-scores (WHO, n.d.-b).

associated with a decrease in the WAZ by 0.07 SD. It is likely that this insignificance is due to the fixed effects absorbing the effects of these variables over time.

Column (2) shows the results of the model that includes both BOD and lagged BOD. While there is no longer a statistically significant relationship between BOD and the WAZ, a 10% increase in lagged BOD is associated with a decrease the WAZ by 0.030 SD. This corresponds to a decrease of approximately 41 grams, or 0.4%, in the weight of the average boy discussed earlier. The finding is consistent with the expectation that exposure to water pollution has a delayed effect on nutritional status. Especially in areas where groundwater is the main resource of drinking water, it may take time before river water pollution reaches drinking water sources. Studies have found that prolonged diarrhea episodes resulting from exposure to contaminants can have a delayed effect on child growth (Moore et al., 2001), and that heavy metals found in polluted water accumulate in the body over time and start to negatively affect it at higher levels (Kampa & Castanas, 2008). Again, only the control variable Age is statistically significant.

4.2 Categorical explanatory variables

As an extension of the main model, the numeric variables BOD and lagged BOD are converted into variables categories representing varying levels of pollution. The categories 'Excellent' (lower than 1 mg/L), 'Good' (between 1 and 2 mg/L), 'Fair' (between 2 and 6 mg/L), and 'Poor' (higher than 6 mg/L) are created. This transformation allows for an examination of how water pollution affects the outcome at different pollution levels.

Table 3 presents the results. The results in Column (1) show that no category of BOD is statistically significant. Column (2) shows the results of the model with the inclusion of both BOD and lagged BOD. Again, the results of BOD are not statistically significant. However, there are negative statistically significant relationships for two categories of lagged BOD. These results further confirm the expectation that lagged water pollution is more meaningful than pollution in the current year. The estimates indicate that a child experiencing lagged pollution levels of fair quality has a WAZ that is 0.68 SD lower than that of a child exposed to water of excellent quality. And, a child experiencing poor pollution levels in the previous year has a 0.92 SD lower WAZ than a child in a district with excellent water quality. The finding that children living in areas with poor river water pollution have a WAZ that is nearly 1 SD lower than those living in areas without river water pollution is striking. To put this into context, a 3-year-old boy moving from a WAZ of 0 (the median, 14.34kg) to one of -0.92 is associated with a decrease in body weight of approximately 1.5 kg, equivalent to a 10.46% decrease in body weight (see Footnote 1 on page 14).

TABLE 2. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND

	Weight-for-age z-score	
	(1)	(2)
BOD current year (log)	-0.26 (0.10)***	-0.09 (0.12)
BOD 1-year lag (log)		-0.30 (0.11)***
Water Source		
Improved	0.04 (0.14)	0.02 (0.14)
Unimproved	0.08 (0.16)	0.04 (0.17)
Water Purification		
Rarely	0.08 (0.10)	0.06 (0.11)
Usually	0.00 (0.12)	-0.02 (0.12)
Always	-0.13 (0.13)	-0.14 (0.14)
Soap Use	-0.01 (0.08)	0.04 (0.08)
Meals	-0.04 (0.06)	-0.03 (0.07)
Age	-0.07 (0.00)***	-0.07 (0.00)***
Household Income (log)	-0.03 (0.05)	-0.04 (0.05)
Household Size	0.01 (0.02)	0.02 (0.02)
Education Head		
Primary	-0.12 (0.14)	-0.13 (0.14)
Middle	-0.09 (0.13)	-0.03 (0.14)
Secondary	-0.07 (0.19)	-0.01 (0.19)
High Secondary	-0.25 (0.25)	-0.32 (0.25)
Bachelor's	0.13 (0.28)	0.04 (0.38)
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes
No. of observations	3,758	3,186
Within R^2	0.1914	0.2026

Notes: Robust standard errors in parentheses. *Significant at $p < 0.1$ level. **Significant at $p < 0.05$ level. *** Significant at $p < 0.01$ level.

TABLE 3. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (CATEGORICAL)

	Weight-for-age z-score	
	(1)	(2)
BOD current year		
Good	-0.02 (0.13)	0.03 (0.16)
Fair	0.01 (0.20)	0.18 (0.20)
Poor	-0.45 (0.30)	-0.28 (0.29)
BOD 1-year lag		
Good		-0.19 (0.12)
Fair		-0.68 (0.16)***
Poor		-0.92 (0.31)***
Controls	Yes	Yes
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes
No. of observations	3,758	3,186
Within R^2	0.1888	0.2093

Notes: Robust standard errors in parentheses. *Significant at p < 0.1 level. **Significant at p < 0.05 level. *** Significant at p < 0.01 level.

4.3 Heterogeneity analyses

To examine whether subsamples experience the effect of water pollution on nutritional status differently, three heterogeneity analyses are conducted. Following Tanaka (2015), regressions are run using subsamples of boys and girls. Another analysis contains subsamples of children with higher- and lower-educated heads of the household. Last, analyses are conducted using subsamples of urban and rural children.

4.3.1 Boys versus girls

First, the potentially heterogenous effect of water pollution on WAZ of boys versus girls is examined. Most research on these gender differences has focused on air pollution. Air pollution has been found to affect adult women more strongly than men, whereas studies on children find that boys are more affected than girls in early childhood (Clougherty, 2010). It influences male fetuses more strongly because they are more susceptible to stress from the mother (Sanders & Stoecker, 2015). Pollution-related diseases could affect boys more as the immune systems of girls have better responses (Bouman et al., 2005).

Table 4a shows the results with the explanatory variables BOD and lagged BOD. Column (1) shows how a 10% increase in BOD reduces WAZ by 0.025 SD when only boys are included in the sample, and reduces it by 0.030 SD when only girls are included, which is similar to the effect sizes found in the main model. Column (2) shows how inclusion of lagged BOD only provides a statistically significant result in the boys subsample, where a 10% increase in lagged BOD decreases the WAZ by 0.039 SD.

TABLE 4A. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (BOYS VS. GIRLS)

	Weight-for-age z-score	
	(1)	(2)
Boys		
BOD current year (log)	-0.25 (0.12)**	-0.07 (0.17)
BOD 1-year lag (log)		-0.39 (0.14)**
Girls		
BOD current year (log)	-0.30 (0.13)**	-0.12 (0.14)
BOD 1-year lag (log)		-0.15 (0.13)
Controls	Yes	Yes
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes

Notes: Robust standard errors in parentheses. *Significant at $p < 0.1$ level. **Significant at $p < 0.05$ level. ***Significant at $p < 0.01$ level.

In Table 4b, the results for subsamples of boys and girls are shown with the categorical pollution variables. According to Column (1), there is no statistically significant effect of the different categories of BOD for neither boys nor girls. Column (2) shows that boys experiencing good, fair or poor pollution levels have a 0.34, 0.76 or 0.96 SD lower WAZ than boys experiencing excellent water quality, respectively. The only statistically significant result for the girls subsample shows that girls exposed to fair water quality levels have a 0.59 SD lower WAZ than girls experiencing excellent levels.

In line with the expectations, the results suggest that boys are affected more by water pollution as statistically significant relationships are more often absent in the girl subsample and effect sizes of significant results in the same categories between the subsamples are generally larger for boys. The effect of numeric BOD in the current year is slightly stronger for girls, but this would translate to a minor difference in reality. Notably, when comparing the gender difference between those exposed to fair water quality versus excellent quality, there is a 0.17 SD lower effect of pollution on WAZ girls than on boys, which is a considerably large difference.

TABLE 4B. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (BOYS VS. GIRLS)

	Weight-for-age z-score	
	(1)	(2)
Boys		
BOD current year		
Good	0.03 (0.16)	0.26 (0.21)
Fair	0.12 (0.24)	0.29 (0.27)
Poor	-0.56 (0.38)	-0.38 (0.43)
BOD 1-year lag		
Good		-0.34 (0.17)**
Fair		-0.76 (0.22)***
Poor		-0.96 (0.34)***
Girls		
BOD current year		
Good	-0.12 (0.16)	-0.23 (0.20)
Fair	-0.17 (0.26)	0.05 (0.25)
Poor	-0.45 (0.39)	-0.23 (0.36)
BOD 1-year lag		
Good		-0.03 (0.17)
Fair		-0.59 (0.21)***
Poor		-0.75 (0.43)*
Controls	Yes	Yes
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes

Notes: Robust standard errors in parentheses. *Significant at $p < 0.1$ level. **Significant at $p < 0.05$ level. ***Significant at $p < 0.01$ level.

4.3.2 Higher- versus lower-educated household heads

Second, the sample is divided into a subsample of households where the head completed no more than primary school, and a subsample where the head at least started middle school. Higher education is associated with better nutrition knowledge (Parmenter et al., 2000). This means children in higher-educated households may receive more benefits from nutrition, thereby altering the way in which water pollution affects the nutritional status of these children.

Table 5a presents the results where the independent variables BOD are in log-form. Column (1) shows that children with lower-educated heads of the household have a 0.034 lower WAZ for a 10% increase in BOD. The higher-educated sample shows no statistically significant result. According to the estimates in Column (2), children in households with lower-educated heads see a 0.032 decrease in WAZ for every 10% increase in lagged BOD, whereas children in households with higher-educated heads have a 0.026 decrease.

TABLE 5A. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (LOWER- VS. HIGHER-EDUCATED HEAD)

	Weight-for-age z-score	
	(1)	(2)
Lower-educated head		
BOD current year (log)	-0.34 (0.13)***	-0.26 (0.17)
BOD 1-year lag (log)		-0.32 (0.15)**
Higher-educated head		
BOD current year (log)	-0.08 (0.16)	0.07 (0.16)
BOD 1-year lag (log)		-0.26 (0.13)**
Controls	Yes	Yes
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes

Notes: Robust standard errors in parentheses. *Significant at $p < 0.1$ level. **Significant at $p < 0.05$ level. ***Significant at $p < 0.01$ level.

Table 5b shows the results with the categorical variables of BOD. The results in Column (1) suggest no statistically significant results. In Column (2), the estimates suggest a 0.77 decrease in WAZ for a child in the lower-educated sample experiencing fair lagged pollution levels compared to a child exposed to excellent levels. A child from the higher-educated sample experiencing fair lagged pollution levels has a 0.46 lower WAZ than a child exposed to excellent levels.

In line with the theoretical expectation, this analysis suggests that children with lower-educated household heads are affected more by water pollution. The results display higher statistical significance and stronger effects for the lower-educated sample. Similar to the boy-girl analysis, children from lower-educated households have a 0.31 lower WAZ than those from higher-educated households when comparing children with fair water quality exposure to those with excellent water quality exposure.

TABLE 5B. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (LOWER- VS. HIGHER-EDUCATED HEAD)

	Weight-for-age z-score	
	(1)	(2)
Lower-educated head		
BOD current year		
Good	0.02 (0.16)	-0.08 (0.29)
Fair	-0.15 (0.29)	0.06 (0.35)
Poor	-0.36 (0.37)	0.00 (0.44)
BOD 1-year lag		
Good		0.04 (0.22)
Fair		-0.77 (0.29)***
Poor		-0.48 (0.54)
Higher-educated head		
BOD current year		
Good	0.02 (0.18)	0.25 (0.23)
Fair	0.18 (0.25)	0.29 (0.27)
Poor	-0.18 (0.56)	-0.67 (0.57)
BOD 1-year lag		
Good		-0.33 (0.17)*
Fair		-0.46 (0.22)**
Poor		-0.71 (0.38)*
Controls	Yes	Yes
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes

Notes: Robust standard errors in parentheses. *Significant at $p < 0.1$ level. **Significant at $p < 0.05$ level. ***Significant at $p < 0.01$ level.

4.3.3 Urban versus rural areas

Next, the sample is divided into children living in urban areas, and those living in rural areas. The literature on the effects of pollution on urban versus rural children is mixed. On the one hand, population density is positively associated with pollution, and higher levels of pollution have been observed in large cities compared to rural areas (Goel, 2006). Kattula et al. (2015) find that diarrhea prevalence was twice as high in urban slums as in rural areas. The authors say this can be explained by the high population density, and inhabitants facing graver environmental threats such as contaminated drinking water and higher levels of pollution. Furthermore, in urban areas, fewer children are exclusively breastfed before the age of 6 months than rural children (Chandhiok et al., 2015). As breastfeeding protects children by decreasing their exposure to contaminants and increasing the efficiency of their immune systems, children are protected from diarrheal diseases they are breastfed longer (VanDerslice et al., 1994). Evidently, when water quality is poor, breastfeeding becomes more important. The combination of these reasons may explain why water pollution would affect urban children more. On the other hand, Brainerd and Menon (2014) find that rural children are more affected by agricultural water pollution. Rural children rely on untreated groundwater sources more often, increasing their exposure to water pollution (Jain et al., 2010). They also face poorer economic and conditions and education attainment (Azam, 2019), which could exacerbate the impact of pollution on health. These findings can lead to an expectation of a stronger effect of water pollution on rural children.

Column (1) in Table 6a shows that current BOD affects children in urban areas strongly and more than those in rural areas, with a 0.06 SD decrease in WAZ for a 10% increase in BOD. However, Column (2) shows that only children in rural areas are affected by lagged BOD, with a 0.026 decrease in WAZ for every 10% increase in lagged BOD.

TABLE 6A. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (URBAN VS. RURAL AREAS)

	Weight-for-age z-score	
	(1)	(2)
Rural area		
BOD current year (log)	-0.23 (0.12)*	-0.16 (0.15)
BOD 1-year lag (log)		-0.26 (0.13)**
Urban area		
BOD current year (log)	-0.60 (0.19)***	-0.10 (0.20)
BOD 1-year lag (log)		-0.35 (0.18)*
Controls	Yes	Yes
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes

Notes: Robust standard errors in parentheses. *Significant at p < 0.1 level. **Significant at p < 0.05 level. ***Significant at p < 0.01 level.

According to the results in Column (1) of Table 6b, urban children experiencing poor levels of BOD in the current year have a 1.94 SD lower WAZ than children exposed to excellent levels. The estimates in Column (2) indicate that rural children experience a 0.65 or 0.87 lower WAZ when lagged water quality is of fair or poor quality compared to excellent quality, respectively. Urban children from districts with poor quality lagged water levels have a 0.97 lower WAZ than those living in areas with excellent quality.

Urban children seem to be very strongly affected by current levels of water pollution, and rural children have more significant results for lagged BOD. This difference can possibly be explained by the fact that rural children rely more on groundwater, and pollution from rivers generally takes longer to leach into groundwater and reach drinking water sources. In urban areas, piped water coverage is higher, allowing potentially poorly treated water from rivers to reach the population faster. The concentration of polluting industries may be higher near the cities where these children live, which could also increase the speed with which pollutants reach children.

TABLE 6B. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (URBAN VS. RURAL AREAS)

	Weight-for-age z-score	
	(1)	(2)
Rural area		
BOD current year		
Good	0.04 (0.17)	-0.05 (0.19)
Fair	0.09 (0.25)	0.08 (0.25)
Poor	-0.19 (0.35)	-0.25 (0.34)
BOD 1-year lag		
Good		-0.01 (0.17)
Fair		-0.65 (0.20)***
Poor		-0.87 (0.32)***
Urban area		
BOD current year		
Good	0.04 (0.20)	0.52 (0.30)*
Fair	-0.38 (0.33)	0.12 (0.27)
Poor	-1.94 (0.60)***	-1.36 (0.72)*
BOD 1-year lag		
Good		-0.36 (0.20)*
Fair		-0.31 (0.25)
Poor		-0.97 (0.38)**
Controls	Yes	Yes
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes

Notes: Robust standard errors in parentheses. *Significant at $p < 0.1$ level. **Significant at $p < 0.05$ level. ***Significant at $p < 0.01$ level.

4.4 Additional robustness checks

4.4.1 Control variables and fixed effects

Table D1 in Appendix D shows the main model without the inclusion of control variables. The results in Column (1) show that a negative relationship between BOD and WAZ remains. It is highly significant and has a coefficient of -0.30, a similar effect size as with the inclusion of the controls. Column (2) shows that without the inclusion of control variables, lagged BOD no longer shows a statistically significant relationship with WAZ. Now, it is current BOD that has a negative significant coefficient of -0.24. It is likely that the controls help mitigate omitted variable bias by capturing some of the variation in WAZ that can be attributed to the controls instead of water pollution. The results after adding controls seem to suggest that pollution has delayed effects on nutritional status.

Table D2 in Appendix D shows the main model where different combinations of fixed effects are added. In Columns (1) no fixed effects are included. There is a slightly lower but statistically significant effect of BOD of -0.10. Notably, many of the control variables are statistically significant. Having an improved water source is associated with a lower WAZ compared to having piped water. Purifying water more often is positively associated as well. A higher number of meals per day increases WAZ, as well as higher income. Household size is negatively associated, and having a head with low education seems to be associated with a decrease in WAZ compared to a head with no education. Column (2) shows that when lagged BOD is added, the BOD variables are no longer statistically significant. Some controls remain significant, and children with a higher-educated head have a higher WAZ compared to children with heads lacking education. Columns (3) shows that adding individual and year fixed effects alters the effect size of BOD in the current year to -0.24, and removes the significance of most of the controls. This could mean that the fixed effects absorb the effects of the controls on WAZ. In Column (4), only lagged BOD is again statistically significant with a coefficient of -0.32. The results remain largely unchanged when including year fixed effects instead of state-by-year fixed effects. This suggests that much of the variation in WAZ is explained by individual- and year-specific factors and that the results are robust to the inclusion of state-specific factors.

4.4.2 Children under 6 months of age

Children younger than 6 months generally do not consume water. However, in India, only 56% of mothers exclusively breastfeeds the child up to 6 months without the supplementation of water or formula (Nishimura et al., 2018). It is difficult to decide which observations to exclude as data on breastfeeding practices is lacking, and children can still be exposed through other pathways, so all of these children were included in the main analysis. To examine whether the results are robust to their exclusion, children under 6 months of age in the current and lagged years are removed from the sample. Tables E1 and E2 in Appendix E present the results.

Column (1) and (2) in Table E1 show that the results remain statistically significant and the effect sizes are similar; in the first model current BOD has a coefficient of -0.26, and in the second model only lagged BOD is statistically significant with a coefficient of -0.30. The effect becomes slightly weaker when the children are excluded, with these coefficients changing to -0.22 and -0.24. This could mean that children under the age of 6 months are still affected by water pollution, perhaps also through other pathways than consumption of food and water if they are exclusively breastfed.

According to the results in Table E2, Column (1) shows that excluding the children gives the 'poor' category of BOD in the current year a statistically significant coefficient of -0.55. The results in Column (2) show that the statistically significant effect sizes of lagged BOD again become slightly weaker when the children are excluded, with the coefficients for the 'fair' category changing from -0.68 to -0.54, and the coefficients for the 'poor' category changing from -0.92 to -0.81. Overall, the results seem quite robust to the exclusion of these children.

4.4.3 2-year lagged water pollution

Appendix F shows the results of the regressions where an additional lag of BOD is included, for the year 2003 and 2010. Children born after 2003 were excluded from the analysis since it is impossible that they were directly exposed to pollution in this year. Column (1) shows that all numeric BOD variables no longer exhibit statistically significant coefficients at the 0.05 level. As for the categorical versions, Column (2) shows that only 1-year lagged BOD keeps a statistically significant coefficient of -0.86 for children experiencing poor water quality levels in their district, which is very similar to the coefficient in the main model. These results seem to indicate that 1-year lagged BOD is still the main determinant of WAZ when it comes to BOD. The lack of significance in the 2-year lagged BOD may be attributed to the fact that the delayed effect of pollution on nutritional status is restricted to a 1-year lag. It is important to note that there are moderate levels of multicollinearity present when the second lag is added, as water pollution levels in consecutive years are correlated. Also, many observations are excluded from the model, which may have affected the results.

5 Conclusion and discussion

This study explored the relationship between river water pollution and child nutritional status in India, which yielded some useful insights. The research question "*To what extent does river water pollution exposure affect child nutritional status in India?*" was answered by means of a multi-way fixed effect regression analysis, drawing on a combination of countrywide IHDS survey and GEMStat river water pollution data that has never been used before in this setting.

The analyses indicate that district-level yearly averages of river water pollution have a negative impact on child nutritional status. The results are in line with previous studies that found negative effects of pollution on child health (Brainerd & Menon, 2014; Garg et al., 2018; Goyal & Canning, 2018; Kim et al., 2016; Minamoto et al., 2005).

This study provides novel insights into the way in which district-level yearly averages of river water pollution affect child health and how its impact differs by sex, household education level and residential area. The results are in line with the expectation that being exposed to water pollution has a delayed effect on nutritional status, as a 10% increase in BOD is associated with a 0.4% decrease in body weight of an average child in the sample one year later. Categorical conversion of the water pollution variables allowed for a more nuanced examination of the relationship. Results showed how children living in districts with fair or poor river water quality in the previous year have a 0.68 or 0.92 SD lower WAZ than those exposed to excellent river water quality. An average child being exposed to poor levels of BOD in the previous year is thus associated with an approximate 10.5% lower WAZ compared to children living in districts with excellent BOD levels. These findings indicate substantially lower nutritional statuses of children living in polluted areas, which can have a significant impact children's development over time. The control variables were generally insignificant for all analyses after the inclusion of the fixed effects, which could mean that the fixed effects absorb the impact these variables have on WAZ. Heterogeneity analyses suggest that boys are generally affected more by pollution from the previous year than girls, and that children with higher-educated of household heads are not as affected by water pollution as those with lower-educated household heads. Children living in urban areas are strongly affected by pollution levels in the same year, whereas children living in rural areas experience stronger effects from last year's pollution, possibly to the delayed effect of pollution infiltration in the groundwater. Results are robust to the exclusion of children under 6 months and the inclusion of state-by-year fixed effects.

Even though this research has robust findings in line with previous studies, this study also has its limitations. As mentioned earlier, this study suffers from endogeneity issues, meaning that the results should be interpreted with caution. Furthermore, the allocation of pollution levels to children is based on the district of residence in 2005; it is possible that some people moved out of district in 2012, which could not be accounted for in this study. However, Bell et al. (2015) found that India has the lowest internal migration out of 61 countries in their study, making this a relatively small concern for this study. Moreover, despite having an advantage over prior studies by using panel data, another limitation of this research is that the relationship could only be examined using two survey years. This also led to the creation of annual averages of BOD rather than monthly values, which would have been more informative as pollution levels can fluctuate during the year (Brainerd & Menon, 2014).

In order to overcome the endogeneity issue, future research could consider potential instrumental variables such as weather patterns or water pollution regulations. Furthermore, the field could benefit from a study which takes into account district-level precipitation and seasonal variation in water pollution, as heavy rains and flooding could affect the relationship as well. Additionally, future studies could include more countries and time periods of survey data, in order to improve our understanding of how water pollution affects child and adult health around the world, over time and throughout the year.

Childhood malnutrition continues to be an important issue in India, and this analysis seems to suggest that district-level river water pollution plays a part. In light of the results of this study, policymakers should address river water pollution especially in areas with higher BOD levels as improving water quality from poor to excellent may deliver substantial positive effects on children's nutritional status. Implementing stricter pollution regulations and setting up initiatives to continuously monitor pollutants in rivers and groundwater can be a stepping stone in reducing the adverse impact on public health. As boys are more vulnerable than girls, health-related policies could focus more on reducing this gender-gap. Setting up programs to raise awareness about water pollution and nutrition in areas with lower educated households may help them gain the nutritional benefits of knowledge. To conclude, when the effects of water pollution are better understood, a healthier living environment can be created. Even though the results of this study should be interpreted cautiously and future research is needed to confirm the findings, children's health may benefit from improvements in water quality, providing them with a stronger foundation for their future.

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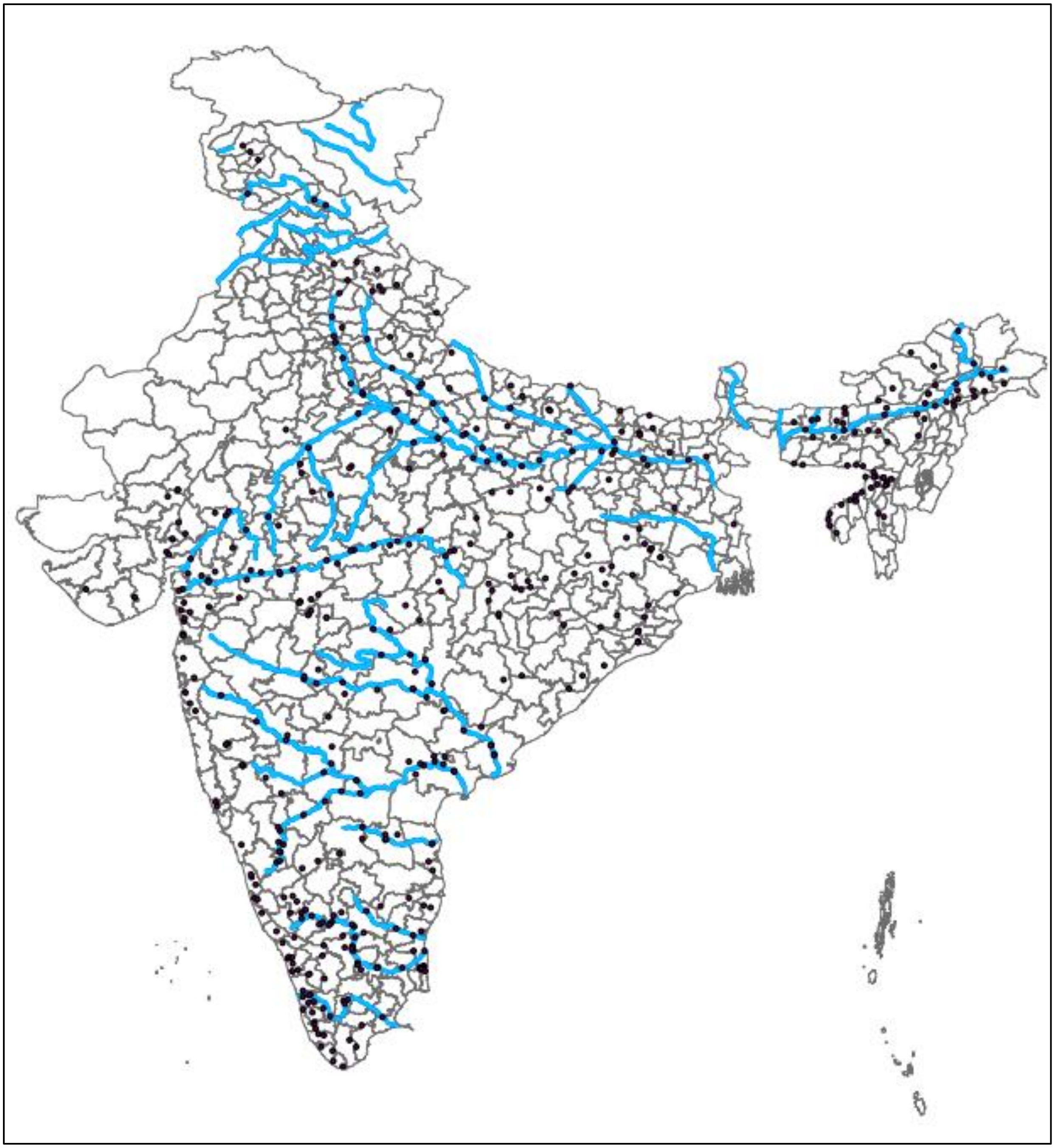
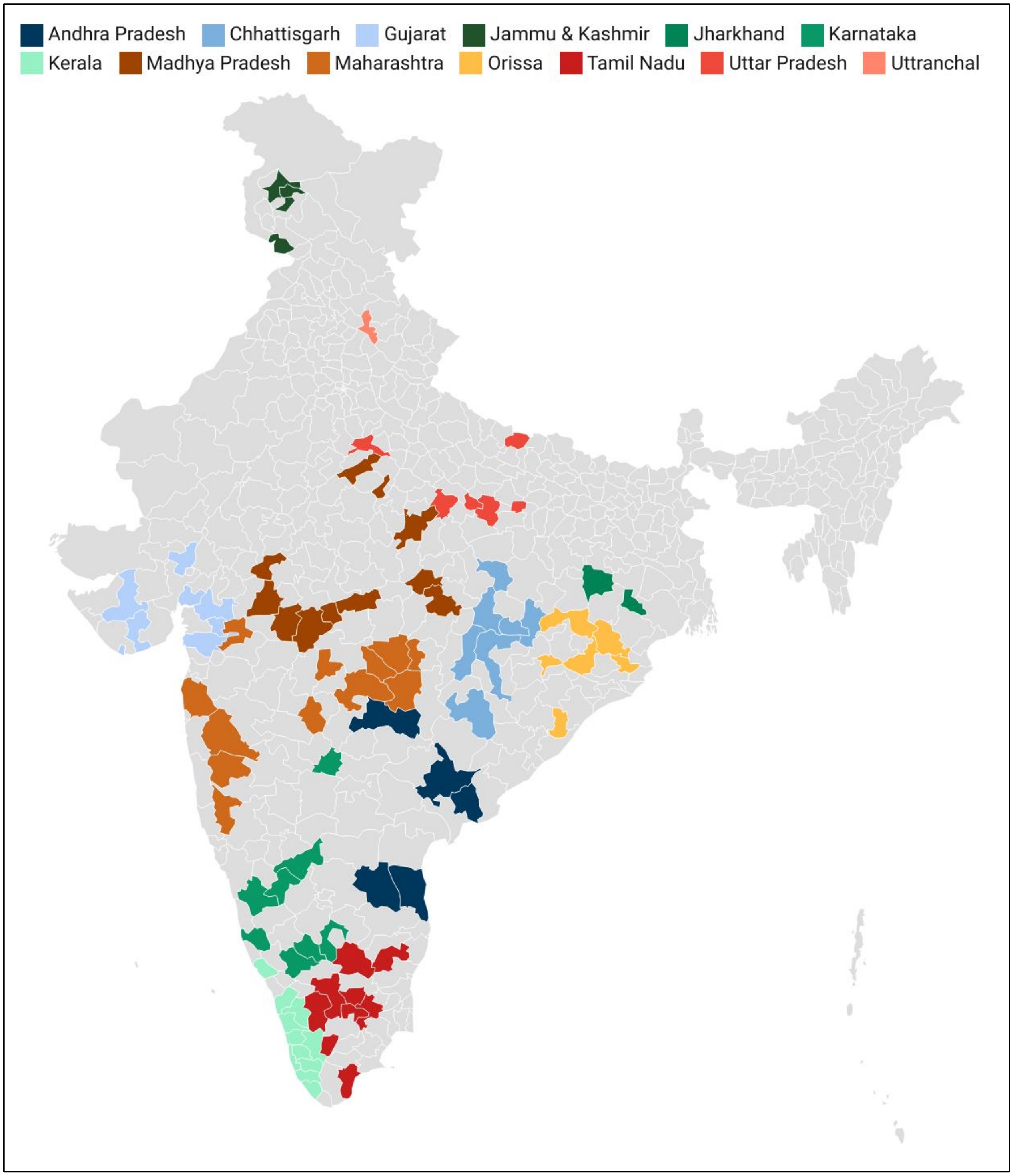
Appendix A



APPENDIX A. MAP OF ALL AVAILABLE WATER STATIONS UP TO 2012. SOURCE: GEMS/WATER DATA CENTRE (2023).

Appendix B



APPENDIX B. MAP OF DISTRICTS (2001 CENSUS) AFTER MERGING THE SAMPLE WITH 2004-05 AND 2011-12 WATER DATA, COLORED BY STATE. CREATED ON WWW.DATAWRAPPER.DE.

Appendix C

TABLE C1. SUMMARY STATISTICS

	2005			2012		
	Obs.	Mean	SD	Obs.	Mean	SD
WAZ	2,508	-2.08	1.81	2,508	-1.83	1.46
BOD current	2,496	2.37	3.18	2,407	2.51	4.30
BOD 1-year lag	2,249	2.30	3.32	2,450	2.35	3.60
BOD 2-year lag	2,000	1.74	2.16	2,448	2.66	3.94
Gender	2,508	1.47	0.50	2,508	1.47	0.50
Age (months)	2,508	35.76	19.00	2,508	119.98	20.77
Water Source	2,504	1.79	0.75	2,508	1.72	0.72
Water Purification	2,472	1.73	1.04	2,497	1.73	1.10
Soap Use	2,484	0.41	0.49	2,480	0.64	0.48
Meals	2,492	2.85	0.69	2,491	2.85	0.60
Income	2,508	90510.11	119551.2	2,508	113596.50	148014.00
Head Education	2,168	1.75	1.50	2,466	2.08	1.56
Household Size	2,508	6.95	3.22	2,508	6.11	2.59
Rural/Urban	2,508	0.30	0.46	2,508	0.33	0.47

TABLE C2. STATE-WISE MEAN WAZ BY YEAR AND GENDER

	WAZ			
	2005		2012	
	Male	Female	Male	Female
Jammu & Kashmir	-0.51	-1.11	-1.08	-1.38
Uttarakhand	-1.59	-1.59	-1.41	-1.14
Uttar Pradesh	-2.77	-2.21	-2.42	-1.90
Jharkhand	-2.29	-1.83	-1.50	-1.32
Orissa	-2.14	-2.30	-2.02	-1.86
Chhattisgarh	-2.47	-2.40	-2.22	-2.21
Madhya Pradesh	-2.50	-2.69	-2.14	-2.16
Gujarat	-2.29	-2.18	-2.07	-1.89
Maharashtra	-1.95	-1.89	-1.83	-1.77
Andhra Pradesh	-2.10	-1.98	-1.96	-1.39
Karnataka	-2.20	-2.09	-1.90	-2.09
Kerala	-1.57	-1.29	-1.04	-1.20
Tamil Nadu	-1.63	-1.44	-1.43	-1.29
Total	**-2.10**	**-2.05**	**-1.85**	**-1.80**

TABLE C3. STATE-WISE MEAN BOD BY YEAR

	BOD						
	2003	2004	2005	2010	2011	2012	**Total**
Jammu & Kashmir	-	-	1.86	1.33	1.11	1.36	**1.42**
Uttarakhand	1.15	1.16	1.17	1.21	1.65	1.30	**1.27**
Uttar Pradesh	2.86	5.75	7.21	7.19	7.41	7.33	**6.29**
Jharkhand	1.25	3.37	2.49	2.67	2.17	3.34	**2.55**
Orissa	0.76	0.82	0.78	1.12	1.17	0.91	**0.93**
Chhattisgarh	2.40	0.99	1.02	1.01	1.18	1.30	**1.32**
Madhya Pradesh	1.39	2.01	1.84	1.69	2.19	1.83	**1.83**
Gujarat	0.99	3.67	3.23	6.50	3.51	3.06	**3.49**
Maharashtra	2.31	2.75	3.08	2.93	1.86	3.86	**2.80**
Andhra Pradesh	1.08	1.04	1.57	2.86	1.19	1.26	**1.50**
Karnataka	1.72	1.69	1.17	2.37	2.32	1.67	**1.82**
Kerala	0.87	0.71	0.55	0.73	0.67	0.68	**0.70**
Tamil Nadu	1.56	1.76	1.60	1.43	1.60	1.48	**1.57**
Total	**1.53**	**2.33**	**2.12**	**2.54**	**2.16**	**2.26**	

TABLE C4. DISTRIBUTION OF MAIN VARIABLES OF INTEREST

	2005		2012	
	Obs.	%	Obs.	%
WAZ				
Underweight (<-2 SD)	1,304	51.99	1,136	45.30
Severely underweight (<-3 SD)	744	29.67	507	20.22
BOD current				
Excellent (<1 mg/L)	835	33.45	866	35.98
Good (1-2 mg/L)	854	34.21	886	36.81
Fair (2-6 mg/L)	650	26.04	540	22.43
Poor (>6 mg/L)	157	6.29	115	4.78
BOD 1-year lag				
Excellent (<1 mg/L)	700	31.12	777	31.71
Good (1-2 mg/L)	812	36.10	941	38.41
Fair (2-6 mg/L)	596	26.50	662	27.02
Poor (>6 mg/L)	141	6.27	70	2.86
Gender				
Male	1,334	53.19	1,334	53,19
Female	1,174	46.81	1,174	46,81
Age groups (years)				
0-1	337	13.44	-	-
2-4	1,432	57.10	-	-
5-7	739	29.47	77	3.07
8-10	-	-	1,193	47.57
11-14	-	-	1,238	49.36

Appendix D

TABLE D1. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (CONTROLS)

	Weight-for-age z-score	
	(1)	(2)
BOD current year (log)	-0.30 (0.09)***	-0.24 (0.11)**
BOD 1-year lag (log)		0.01 (0.09)
Controls	No	No
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes
No. of observations	4,490	4,048
Within R^2	0.0058	0.0036

Notes: Robust standard errors in parentheses. *Significant at p < 0.1 level. **Significant at p < 0.05 level. ***Significant at p < 0.01 level.

TABLE D2. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (FIXED EFFECTS)

	Weight-for-age z-score			
	(1)	(2)	(3)	(4)
BOD current year (log)	-0.10 (0.05)**	-0.14 (0.09)	-0.24 (0.10)**	-0.07 (0.11)
BOD 1-year lag (log)		0.07 (0.08)		-0.32 (0.10)***
Water Source				
Improved	-0.24 (0.07)***	-0.22 (0.07)***	0.04 (0.14)	0.01 (0.15)
Unimproved	-0.13 (0.09)	-0.11 (0.09)	0.05 (0.15)	-0.00 (0.16)
Water Purification				
Rarely	0.10 (0.10)	0.12 (0.11)	0.05 (0.10)	0.02 (0.10)
Usually	0.24 (0.11)**	0.22 (0.11)*	-0.04 (0.11)	-0.05 (0.12)
Always	0.43 (0.11)***	0.43 (0.11)***	-0.21 (0.13)*	-0.20 (0.13)
Soap Use	0.14 (0.07)*	0.10 (0.08)	0.04 (0.08)	0.08 (0.08)
Meals	0.15 (0.05)***	0.17 (0.06)***	-0.01 (0.07)	-0.03 (0.07)
Age	-0.00 (0.00)	-0.00 (0.00)	-0.07 (0.00)***	-0.07 (0.00)***
Household Inc. (log)	0.19 (0.03)***	0.18 (0.03)***	-0.05 (0.05)	-0.06 (0.05)
Household Size	-0.05 (0.01)***	-0.04 (0.01)***	0.01 (0.02)	0.02 (0.02)
Education Head				
Primary	-0.25 (0.10)**	-0.20 (0.10)**	-0.11 (0.14)	-0.13 (0.15)
Middle	-0.16 (0.07)**	-0.13 (0.07)*	-0.06 (0.13)	-0.01 (0.14)
Secondary	-0.03 (0.09)	-0.01 (0.09)	-0.05 (0.18)	-0.01 (0.19)
High Secondary	-0.06 (0.10)	-0.02 (0.11)	-0.22 (0.24)	-0.30 (0.25)
Bachelor's	0.21 (0.13)	0.31 (0.14)**	0.18 (0.27)	0.08 (0.28)
Controls	Yes	Yes	Yes	Yes
Individual FE	No	No	Yes	Yes
Year FE	No	No	Yes	Yes
State-by-year FE	No	No	No	No
No. of observations	4,345	4,030	3,758	3,186
Within R^2	0.0685	0.0697	0.1852	0.2016

Notes: Robust standard errors in parentheses. *Significant at $p < 0.1$ level. **Significant at $p < 0.05$ level. ***Significant at $p < 0.01$ level.

Appendix E

TABLE E1. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (CHILDREN <6 MONTHS)

	Weight-for-age z-score	
	(1)	(2)
<6 months included		
BOD current year (log)	-0.26 (0.10)***	-0.09 (0.12)
BOD 1-year lag (log)		-0.30 (-0.11)***
<6 months excluded		
BOD current year (log)	-0.22 (0.09)**	-0.06 (0.13)
BOD 1-year lag (log)		-0.24 (0.11)**
Controls	Yes	Yes
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes

Notes: Robust standard errors in parentheses. *Significant at p < 0.1 level. **Significant at p < 0.05 level. ***Significant at p < 0.01 level.

TABLE E2. WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (CHILDREN <6 MONTHS)

	Weight-for-age z-score	
	(1)	(2)
<6 months included		
BOD current year		
Good	-0.02 (0.13)	0.03 (0.16)
Fair	0.01 (0.20)	0.18 (0.20)
Poor	-0.45 (0.30)	-0.28 (0.29)
BOD 1-year lag		
Good		-0.19 (0.12)
Fair		-0.68 (0.16)***
Poor		-0.92 (0.31)***
<6 months excluded		
BOD current year		
Good	-0.08 (0.12)	-0.00 (0.17)
Fair	-0.02 (0.18)	0.08 (0.21)
Poor	-0.55 (0.27)**	-0.52 (0.31)*
BOD 1-year lag		
Good		-0.23 (0.14)*
Fair		-0.54 (0.18)***
Poor		-0.81 (0.29)***
Controls	Yes	Yes
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes

Notes: Robust standard errors in parentheses. *Significant at $p < 0.1$ level. **Significant at $p < 0.05$ level. ***Significant at $p < 0.01$ level.

Appendix F

WEIGHT-FOR-AGE AND BIOCHEMICAL OXYGEN DEMAND (2-YEAR LAG)

	Weight-for-age z-score	
	(1)	(2)
BOD current year (log)	-0.05 (0.16)	
BOD 1-year lag (log)	-0.22 (0.13)*	
BOD 2-year lag (log)	0.05 (0.07)	
BOD current year		
Good		-0.02 (0.20)
Fair		0.12 (0.24)
Poor		-0.45 (0.39)
BOD 1-year lag		
Good		-0.11 (0.15)
Fair		-0.48 (0.25)*
Poor		-0.86 (0.35)**
BOD 2-year lag		
Good		-0.12 (0.14)
Fair		0.01 (0.24)
Poor		0.03 (0.28)
Individual FE	Yes	Yes
State-by-year FE	Yes	Yes
No. of observations	2,376	2,376
Within R^2	0.1914	0.2026

Notes: Robust standard errors in parentheses. *Significant at $p < 0.1$ level. **Significant at $p < 0.05$ level. ***Significant at $p < 0.01$ level.