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# Seasonal effects of water quality: The hidden costs of the Green Revolution to infant and child health in India ☆

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ABSTRACT

This paper examines the impact of fertilizer agrichemicals in water on infant and child health using water quality data combined with data on child health outcomes from the Demographic and Health Surveys of India. Because fertilizers are applied at specific times in the growing season, the concentrations of agrichemicals in water vary seasonally and by cropped area as some Indian states plant predominantly summer crops while others plant winter crops. Our identification strategy exploits the differing timing of the planting seasons across states and differing seasonal prenatal exposure to agrichemicals to identify the impact of agrichemical contamination on various measures of child health. The results indicate that children exposed to higher concentrations of agrichemicals during their first month experience worse health outcomes on a variety of measures; these effects are largest among the most vulnerable groups, particularly the children of uneducated poor women living in rural India.


## 1. Introduction

The Green Revolution in India transformed the country from one heavily reliant on imported grains and prone to famine to a country largely able to feed itself and successful in achieving its goal of food security. Yields of the country's main crops, wheat and rice, increased dramatically and farmers prospered from the use of Green Revolution technologies including high-yield variety seeds, irrigation, pesticides and nitrogenous fertilizer. The growth in agricultural production improved the well-being of millions of Indians by reducing the incidence of hunger and raising the living standard of the rural poor, but it also exacted a toll on the country's environment. In particular, the heavy use of fertilizers to increase yields led to high levels of toxicity and contamination of surface and ground water in India.

This paper examines the impact of fertilizer agrichemicals in water on infant and child health in India. We study agro-contaminants in water as it is considered to be a reliable measure of human exposure, and use data on water quality from monitoring stations run by India's Central Pollution Control Board (CPCB) combined with data on the health outcomes of infants and children from the 1992–93, 1998–99, and 2005–06 Demographic and Health Surveys (DHS) of India. We focus on fertilizers because they have relatively clear application times, unlike pesticides which may be used (based on need) throughout the crop cycle.[2] Because fertilizers are applied early in the growing season and residues may subsequently seep into water through soil run-off, the concentrations of agrichemicals in water vary seasonally; water contamination also varies regionally by cropped area in India because states in

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[2] Furthermore, unlike fertilizer, pesticide use in India has remained relatively stable across the years we analyze. Moreover, note that our measure of fertilizer includes the agrichemicals that comprise pesticides.

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northern India plant predominantly winter crops while southern Indian states plant mainly summer crops. Our identification strategy exploits the increase in fertilizer use over time in India, the differing timing of the crop planting seasons across India's states, and the differing seasonal prenatal exposure of infants and children to identify the impact of fertilizer agrichemical contaminants in water on various measures of child health.

Our analysis of the effects of agrichemicals provides several noteworthy results. We find that the presence of fertilizer chemicals in water in the month of conception significantly increases the likelihood of infant mortality, particularly neo-natal mortality. The presence of toxins in water in the first month is also significantly associated with reduced height-for-age and weight-for-age z scores for children below five years of age. These effects are most pronounced among vulnerable populations, in particular the children of uneducated poor women living in rural India.

Evaluating the link between water agrichemical contamination and child health in India is important for several reasons. First, in rural India, women form 55–60% of the agricultural labor force and are often at the forefront of farming activities. This suggests that they are directly exposed to chemical applications that are made to the soil to improve productivity; their children are exposed both in utero and after birth to these toxins and at these young ages are highly vulnerable to environmental insults. This exposure may contribute to the relatively poor indicators of child health in India: Indian children have one of the highest rates of stunting and wasting among all developing countries. These rates are higher than predicted given the level of per capita income and infant mortality rates in the country.[3] Second, since water is motile, high levels of chemical contaminants in water have the potential to affect individuals outside of farming communities. Third, evidence from biomedical studies indicates that seasonal exposure to water toxins can affect health outcomes not only in the current population but also in subsequent generations. For example, illnesses such as coronary heart disease — which have been shown to be more likely in adults who as babies were of low-birth weight — are inheritable and may be bequeathed to subsequent generations. Such transmission occurs even without any additional exposure to the chemical contaminants that caused the health problems in the preceding generation. The importance of fetal health is emphasized in Behrman and Rosenzweig's (2004) study which demonstrates that fetal nutrition as measured by birth-weight is a significant determinant of adult earnings. With a few exceptions, the impact of water pollution on all of these dimensions of health in developing countries has largely been neglected in the economics literature, as we discuss below.

The paper is structured as follows. The next section provides a brief overview of the economics, public health and biomedical literature on pollution and child health outcomes in developed and developing countries. The section that follows describes the implementation and impact of the Green Revolution in India, the features of the planting and growing seasons of rice and wheat which we exploit in the paper, and water quality and its regulation in India. We then describe our methodology and data and present our results. Robustness checks are presented thereafter, followed by an analysis of heterogeneity in the impact of water pollution on various subgroups of the population. The paper concludes with a discussion of implications for policy.

## 2. Previous literature

This research fits into several strands of literature in economics. An active area of current research examines the impact of air pollution and other contaminants on infant mortality and child health in developed countries. Many of these studies focus on the United States and use the discontinuity in air pollution created by plausibly exogenous events such as the Clean Air Act, economic recession which reduces industrial activity and emissions, and the introduction of electronic tolls on highways which reduced idling time and car exhaust for identification. These studies document a statistically significant and quantitatively large effect of reduced air pollution on infant and child health (Chay and Greenstone, 2003; Currie and Walker, 2011; Sanders and Stoecker, 2011).[4] Other papers analyzing the impact of negative health shocks on infants in utero, such as exposure to the 1918 influenza epidemic and radiation fallout from the 1986 Chernobyl disaster (Almond, 2006; Almond et al., 2009), further confirm the vulnerability of infants to prenatal exposure to contaminants and underscore the long-lasting effects such exposure can have, extending well into adulthood.[5]

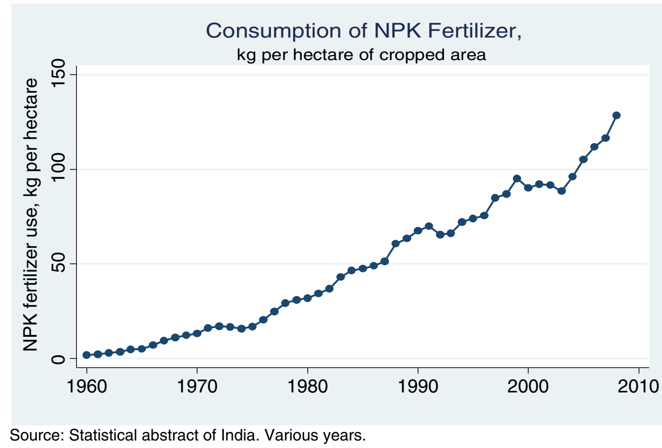


**Fig. 1.** Trend in consumption of NPK fertilizer in India.
Source: Statistical abstract of India. Various years.

Relatively few studies have examined the impact of pollution on health in developing countries, and these have primarily considered the effects of air pollution on child and adult health (for example, Arceo-Gomez et al., 2012; Jayachandran, 2009; Pitt et al., 2006). The work most closely related to ours is Greenstone and Hanna (2011) which assesses the impact of air and water quality regulations on infant mortality across Indian cities for the years 1986–2005. Using air and water pollution data from India's CPCB combined with data on air and water quality regulations, they find that air quality regulations significantly reduced air pollution, which in turn led to a statistically insignificant reduction in infant mortality. However, the water pollution regulations have been ineffective at reducing measures of surface water pollution. As these authors discussed, the implementation of the water quality policies appears to be weak and underfunded in India; the paper does not investigate the effect of fertilizer agrichemicals in water.

A second strand of literature examines the contributions of public health measures (e.g., reduced exposure to lead; enhanced water quality) to improvements in population health. Studies in this area include that of Cutler and Miller (2005), which demonstrates that access to clean water through filtration and chlorination was associated with large reductions in infant and child mortality between 1900 and 1936 in the United States. Similarly, the privatization of local water companies in Argentina in the 1990s was associated with increased access to clean water and significant reductions in child mortality (Galiani et al., 2005). Other recent papers, including those of Zhang (2012) and Ebenstein (2012), document the health impacts of improved water quality in China.

[3] See Deaton and Drèze (2009) for a discussion of the relatively low anthropometric indicators for Indian children.

[4] See Almond and Currie (2010) for a comprehensive review of this literature.

[5] Currie and Vogl (2012) provide a detailed survey of the literature on the impact of early-life health shocks on adult outcomes in developing countries. Recent papers in this line of research include Maccini and Yang (2009) and McEniry and Palloni (2010).

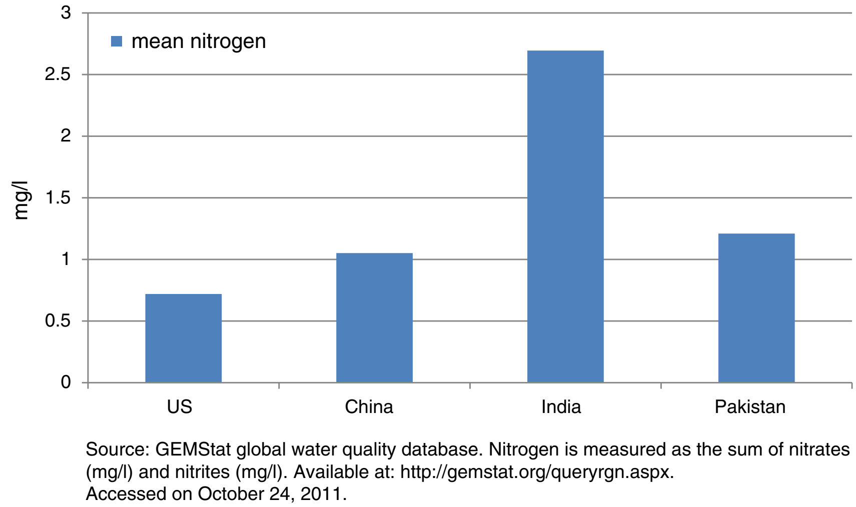


**Fig. 2.** Cross-country comparison of the prevalence of nitrogen in water from 1980–1996.
Source: GEMStat global water quality database. Nitrogen is measured as the sum of nitrates (mg/l) and nitrites (mg/l). Available at: http://gemstat.org/queryrgn.aspx. Accessed on October 24, 2011.

Biomedical studies in developed countries document the relationship between chemicals in water and risks to adult and infant health relatively well. Winchester et al. (2009) show that in the United States there is a significant correlation between seasons of high agrichemical content in water and total birth defects. Garry et al. (2002) find that in Minnesota, pesticide applicators had children with high rates of specific birth defects, and that the risk was most pronounced for infants conceived in the crop-sowing spring months of April to June. Public health studies of poor water quality in developing countries include those of Heeren et al. (2003) and Restropo et al. (1990). Heeren et al. (2003) report a positive correlation between agricultural chemical exposure and birth defects in South Africa, whereas Restropo et al. (1990) analyze the prevalence of abortions, prematurity, and stillbirths among female workers and wives of male workers employed in the floriculture industry of Colombia where pesticide use is widespread. Given resource constraints and high contamination levels, it is likely that the damaging impacts of agrichemicals in water are more pronounced in poor countries such as India.[6] An evaluation of this topic using the lens of economics is thus highly relevant.

## 3. The Green Revolution, agriculture, and water quality in India

At independence in 1947, agriculture in India was characterized by labor-intensive subsistence farming methods that resulted in low yields and continued vulnerability to inadequate food supplies. The country had suffered a devastating famine — the Bengal famine of 1943 — in which an estimated two to four million people died; this famine was later the subject of Amartya Sen's seminal work on famines (Sen, 1977). Indian leaders considered food security to be of paramount importance after independence and implemented programs to achieve this goal, including promotion of modern farming techniques broadly referred to as the "Green Revolution." These techniques were implemented across many developing countries, including India, beginning in the mid-1960s. Green Revolution methods primarily entailed (i) increased area under farming; (ii) increased use of irrigation; (iii) double-cropping, that is planting two crops rather than one annually; (iv) adoption of high-yield variety (HYV) seeds; and (v) significantly increased use of inorganic fertilizers and pesticides.

HYV seeds can increase crop yields by two to four times those of indigenous seeds, but they require more fertilizer and water than do indigenous seeds. Besides high yields, these seeds also have a shorter growing cycle than traditional seeds and thus in some areas crops may be planted twice. The main HYV seeds used in India were wheat (K68) and rice (IR8, or "Miracle Rice"). The diffusion of HYV seeds proceeded rapidly in India, particularly for wheat; for example the share of acreage under wheat sown with HYV seeds increased from 4.1% in the first year of the program (1966–67) to 30.0% only two years later. Over the same period, consumption of nitrogenous fertilizer increased from 658,700 metric tons to 1,196,700 metric tons, and consumption of phosphatic and potassic fertilizers increased in similar proportions (Chakravarti, 1973).

Production of the country's main crops, wheat and rice, increased dramatically after the Green Revolution. Over a span of thirty years from 1960 to 1990, wheat production increased by more than five times (from 10 million tons to 55 million tons) and there was a greater than two-fold increase in rice production (from 32 million tons to 74 million tons).[7] India became a net exporter of rice and wheat in 1978 (Chand, 2001) and famine has not reappeared in the country since independence. At the same time, consumption of synthetic nitrogen-based fertilizers such as urea and nitrogen–phosphate–potassium (NPK) fertilizers rose almost nine-fold in India from the early 1960s to 2003–2004.[8] Fig. 1 illustrates the rapid increase in the use of NPK fertilizers per hectare under cultivation between 1960 and 2008. These fertilizers are heavily subsidized by the Government of India and recent research suggests that the large subsidies are directly responsible for their overuse.[9]

The liberal use of agrochemicals has worked in tandem with rapid industrial growth in recent times to lead to high levels of water pollution in India. Water quality is monitored by India's CPCB which was established in 1974 as part of the Water Act of 1974. This legislation represented India's first effort to reduce water pollution and focused primarily on reducing industrial water pollution and extending sewage treatment facilities rather than reducing the prevalence of agrochemicals. As discussed in Greenstone and Hanna (2011), the water quality regulations have had a negligible impact to date mainly because of weak implementation.

[6] Indeed we find suggestive evidence that the probability of having a prematurely born child is positively associated with the level of nitrogen in water.

[7] Directorate of Economics and Statistics, Dept. of Agriculture and Cooperation, Ministry of Agriculture, India.

[8] Tewatia and Chanda (2005). "Fertilizer Use by Crop," in Fertilizer Use by Crop in India. Rome: Food and Agriculture Organization of the United Nations. Chapter 4.

[9] Chattopadhay et al. (2009). Subsidizing Food Crisis. Bangalore: Greenpeace India. See Bardhan and Mookherjee (2011) for an analysis of one of the subsidized farm input programs implemented in West Bengal from 1982 to 1995, which included provision of HYV seeds, pesticides, and fertilizers.

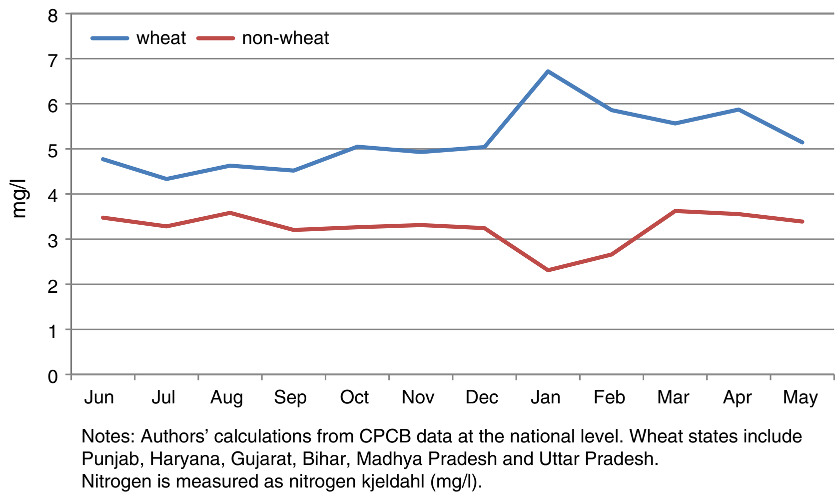


**Fig. 3.** Mean nitrogen concentration in water by month from 1978 to 2005 for wheat. Notes: Authors' calculations from CPCB data at the national level. Wheat states include Punjab, Haryana, Gujarat, Bihar, Madhya Pradesh and Uttar Pradesh. Nitrogen is measured as nitrogen kjeldahl (mg/l).

Although a cross-country comparison of water quality may in general be inappropriate given differing regulations and circumstances, it serves to paint a picture of water contamination in India relative to other countries. As noted in Greenstone and Hanna (2011), water pollution concentrations in India are higher than in other countries such as China and the United States. Focusing specifically on nitrogen (the primary composite of fertilizers such as NPK) measured in milligrams per liter (mg/l), Fig. 2 shows that the average nitrogen level in Indian water bodies is significantly higher than in the U.S. and China over a comparable time period. India's dominance in nitrogen consumption is evident even in relation to Pakistan, a neighbor that shares agricultural and socio-economic practices with India.

Moreover, the concentration of agrochemicals in water is likely to be higher in months in which crops are sown. In the Netherlands, atrazine concentration peaks in June, the month when the herbicide of which it is a component is applied for weed control purposes (Carr and Neary, 2008). In the United States, Winchester et al. (2009) demonstrate that nitrate concentration in surface water is at its peak level in the spring months of April to June when crops are sown. A similar pattern is evident in our water data for India. This is illustrated in Figs. 3 and 4 which portray monthly data on the levels of nitrogen and phosphate concentration in water by type of agricultural region. The bulk of wheat production in India occurs in the northern states of Uttar Pradesh, Punjab, Haryana, Bihar, Madhya Pradesh and Gujarat. Wheat is a *rabi* (winter) crop sown beginning in November through to April and harvested from late spring onwards. As illustrated in Fig. 3, nitrogen concentrations peak in January in the wheat-producing states but not in other areas, as expected. Most rice production in India occurs in the southern states of Andhra Pradesh, Tamil Nadu and Kerala and in the eastern states of Orissa, West Bengal and Assam; rice is a *kharif* (summer) crop and is mostly sown in June–August and reaped in autumn. Fig. 4 shows that phosphate concentrations peak in September in the rice-producing states.[10] It is these differences in soil endowments across the country, making some states more suitable for rice production and others for wheat production, and differences in the timing of crop cycles for these two main crops which allow us to identify the impact of water agro-toxins on infant and child health.

## 4. Identification methodology

The main question is whether infants and children conceived in months when fertilizer agrichemicals in water are at their highest levels (the early cropping season in wheat and rice producing regions) face greater risk of negative health outcomes such as infant mortality and low height-for-age and weight-for-age z scores as of age five. In its basic form, this may be answered by estimating the following empirical specification:

$$\begin{aligned} H_{ijt} = {} & \beta_0 + \beta_1 F_{jtm_c} + \beta_2 P_{jtm_c} + \beta_3 X^c_{ijt} + \beta_4 X^w_{ijt} + \beta_5 X^h_{ijt} + \beta_6 X^{HH}_{ijt} + \beta_7 X_{jt} \\ & + \beta_8 M + \beta_9 T + \beta_{10} S_j + \beta_{11}\left(M\,x\,S_j\right) + \beta_{12}\left(T\,x\,S_j\right) + \varepsilon_{ijt} \end{aligned} \tag{1}$$

where $\underline{H}_{ijt}$ denotes a health outcome for child $i$ in state $j$ in year $t$, $F_{jtm_c}$ denotes the average of a dummy variable that measures the presence of fertilizer agrichemicals in water in the state and year in $m_c$, the month of conception, and $P_{jtm_c}$ is a general measure of water quality that reflects industrial activity and human presence in the state and year in $m_c$; the construction of these variables is described in detail below. $X^c_{ijt}$ are child-specific indicators (order of birth, gender), $X^w_{ijt}$ are woman (mother)-specific indicators (measures of maternal risk factors such as tobacco use and work characteristics, and mother's demographic characteristics including age, education, and general health), $X^h_{ijt}$ are husband (father)-specific indicators (age, education, and type of work), $X^{HH}_{ijt}$ are household-specific indicators (rural/urban indicator, age and gender of household head, household religion and caste, indicator for access to electricity and ownership of assets such as refrigerators, televisions, and motorcycles as well as information on sources of drinking water), and $X_{jt}$ are state-specific indicators (per capita net state domestic product, annual rainfall, average temperature). In order to control for month and year-specific time trends and state-level heterogeneity, Eq. (1) includes month dummies (M), year dummies (T), state dummies ($S_j$), and interactions of month and state dummies and year and state dummies. $\varepsilon_{ijt}$ is the standard idiosyncratic

[10] We present a graph for phosphate concentrations for rice since nitrogen is very soluble in water (Tonn, 2004) and the cultivation of rice involves two stages — sowing and transplantation — both of which are water-intensive. Since phosphates are relatively less soluble in water, a distinct peak in its concentration is evident in rice-producing states compared to other states. Further, the sowing season for rice is less clear-cut as compared to wheat. There could be several rice harvests in a year, particularly in southern India where soil and climate are more amenable. We focus on the *kharif* crop for rice in this figure as this is the largest harvest. This also contributes to the lack of discernible pattern in nitrogen in rice states since the *kharif* season coincides with the arrival of the monsoons in the rice growing states. As noted in Ebenstein et al. (2011), rainfall may dilute the presence of agrichemicals by supplying clean water.

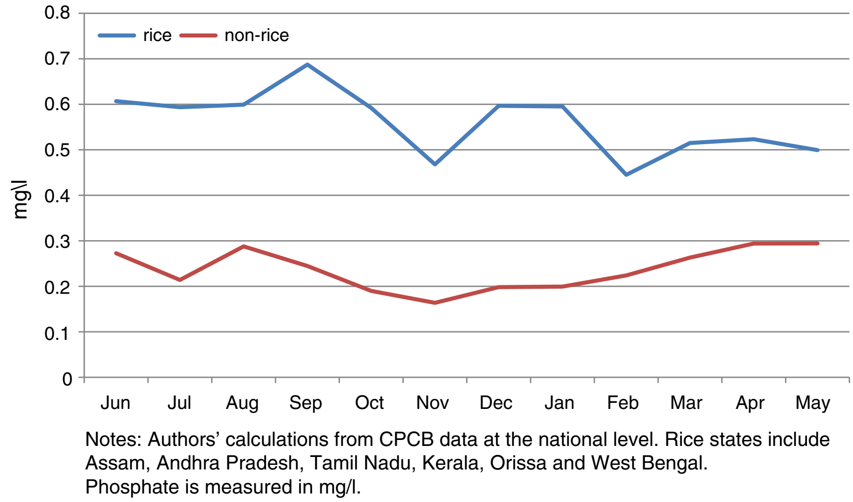


**Fig. 4.** Mean phosphate concentration in water by month from 1978 to 2005 for rice. Notes: Authors' calculations from CPCB data at the national level. Rice states include Assam, Andhra Pradesh, Tamil Nadu, Kerala, Orissa and West Bengal. Phosphate is measured in mg/l.

error term. The coefficient of interest is $\beta_1$: the impact of fertilizer agrichemicals in the month of conception on child health outcomes.[11]

The variable $F_{jtm_c}$ is our measure of the presence of fertilizer agrichemicals in water in a given state and year in the month of conception. The water quality data, which is at the state, year and month level, does not contain a direct measure of fertilizer agrichemicals. Given this, we construct a variable that denotes the presence of agrichemicals using information on the main chemical components of fertilizers in India. This is accomplished by creating dummy variables that indicate the presence in water (at the state, year and month level) of any of the seven main fertilizer components in an amount exceeding the threshold levels defined for drinking water. The main fertilizer components in India are nitrogen, nitrates, nitrites, phosphates, potassium, fluoride and chromium, all of which are measured in the water quality data. Thresholds for drinking water for these agrichemicals are obtained from the U.S. Environmental Protection Agency (EPA) since the CPCB's thresholds for drinking water are defined over time only for coliform, pH, dissolved oxygen and biochemical oxygen demand, and not for the nutrients that constitute agrichemicals.[12] This procedure results in seven dummy variables — one for each of the main fertilizer components — for each state, month, and year over the 1978 to 2005 time span of the data. These seven dummy variables are then averaged at the state, year, and month level, resulting in the variable $F_{jtm_c}$ which has a mean of 0.45 over the entire sample. $P_{jtm_c}$, the general measure of water quality, is the level of biochemical oxygen demand (BOD) in a state, year, and month, which is in continuous form and is directly measured in the water data in milligrams per liter.[13] BOD is included in the regressions so that its absence does not bias the effect of the agrichemical variable.

For a variety of reasons it is likely that our key variable of interest, $F_{jtm_c}$, is correlated with the error term in Eq. (1).[14] First, the fertilizer components that underlie $F_{jtm_c}$ are measured with error: in the early years of water monitoring the measurement technology was relatively primitive and not all agrichemicals and general water pollutants were evaluated (1979–1987); the number of monitoring stations has also increased significantly over time, from 188 in 1979–1987 to 870 as of 2005. Thus earlier measures of water quality are unlikely to accurately portray ground realities at an all-India level. Moreover, unlike BOD which is recorded directly, we construct an indicator for the presence of fertilizer agrichemicals in water based on the chemical composition of fertilizers as described above. As a constructed variable, our indicator for agrichemicals is especially prone to errors in measurement. Finally, lacking information on the district of residence of women and their children in the DHS data, we match demographic data to the water data on the basis of state of residence. The use of state-level information is a proxy for the level of toxins women and children are exposed to in their environment; the use of this proxy may result in additional errors.

In addition to measurement error, the fertilizer indicator is also likely correlated with the error term in Eq. (1) due to simultaneity and omitted variables. For example, suppose water quality monitors were not randomly allocated but were placed, as is likely to be the case, in the most polluted areas with the worst child health outcomes. Then in addition to attenuation bias resulting from classical measurement error, bias may result from the simultaneous causality between poor child health outcomes and pollution monitoring. Omitted variables could bias our coefficient of interest as well. For example, suppose the Indian government targets states with the worst indicators of child nutrition for additional agricultural subsidies to increase food production. Agricultural subsidies are then correlated with both child health outcomes and fertilizer utilization, biasing the coefficient $\beta_1$.

We use instrumental variables to isolate the exogenous component of agrichemicals and BOD, allowing us to consistently estimate $\beta_1$ and $\beta_2$ in Eq. (1) in the presence of endogeneity between these variables and child health outcomes. The identifying instruments that we use are the interactions of cropped area (the area planted in the state with rice normalized by total state area; the area planted in the state with wheat normalized by total state area) and crop sowing months (an indicator for months of the year when rice and wheat are sown in different states of India). Since planting seasons across India's states do not coincide for these main crops, this is a source of exogenous variation in exposure that may be exploited to establish causal links between

[11] We focus on the month of conception due to evidence that the early stages of gestation are the most critical for fetal development vis-à-vis these particular toxins. In particular, Manassaram et al. (2006) note that nitrates and nitrites may travel through the placenta to affect the fetus in the first trimester. The separation of blood circulation between mother and fetus is achieved only from the beginning of the second trimester of pregnancy when the placental membrane becomes adequately developed. To check sensitivity of results to toxin exposure at different points in the gestation cycle, we also consider the impact of water pollutants on measures of child health during the first, second, and third trimesters. These results are discussed below.

[12] Information on the components of fertilizers is available from India's Department of Fertilizer under the Ministry of Chemicals and Fertilizers (http://fert.nic.in/aboutfert/aboutfertilizers.asp). Thresholds for drinking water are obtained from the EPA website at http://water.epa.gov/drink/contaminants/basicinformation/index.cfm.

[13] See Sigman (2002) for a discussion of the benefits of using BOD as a general measure of water pollution. There may be some overlap between agrichemicals and BOD, but not perfectly so. BOD measures the amount of oxygen required in the decomposition of organic matter, and its main source is sewage and industrial activity.

[14] Many of these concerns also apply to $P_{jtm_c}$.

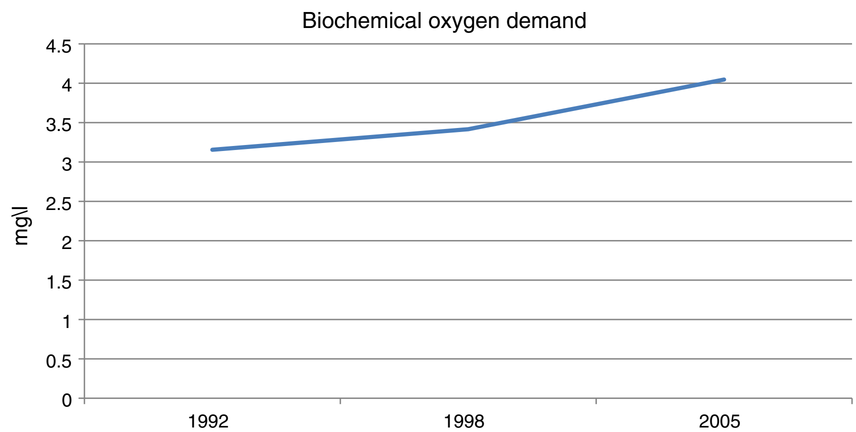


**Fig. 5.** Trend in biochemical oxygen demand over time. Notes: Author's calculations from CPCB data at the national level. Figure shows mean level over all available states for each of the three DHS years analyzed. Biochemical oxygen demand is measured in milligrams (mg) per liter (l).

water agro-contaminants (and the broader measure of water quality) and child health. Our two stage least squares model is of the standard form in which the first stage (shown for agrichemicals and written as a function of the identifying instruments only) is:

$$F_{jtm_c} = \gamma_0 + \gamma_1 \left( R_{jt} \; x \; M^R \right) + \gamma_2 \left( W_{jt} \; x \; M^W \right) + \vartheta_{ijt} \tag{2}$$

$R_{jt}$ and $W_{jt}$ denote normalized cropped area for rice and wheat, respectively: for each state $j$, $R_{jt}$ denotes the area planted with rice (in hectares) in each year $t$ normalized by total state area, and $W_{jt}$ is the area planted with wheat in a state in each year normalized by total state area (these are continuous variables). Hence each state will have variations in values of $R_{jt}$ and $W_{jt}$ depending on whether it has comparative advantage in wheat or rice production. For example, a large rice-producing state like Andhra Pradesh in the south will have a relatively high value for $R_{jt}$ in comparison to $W_{jt}$ over time while the opposite will be true for a large wheat-producing state like Punjab in the north. These cropped area variables capture exposure, with larger cropped areas being tied to greater exposure of a state's population to fertilizer agrichemicals in water. Planting seasons are indicated by the variables $M^R$ and $M^W$, which are dummy variables for the months of the year when rice and wheat crops are sown in each state, respectively. Indian crop calendars identify the months that each crop is planted in each state; even among states that plant the same crops, the planting season can vary.[15] For example, although Punjab plants autumn rice from May to August in each year, the planting season for this crop extends from March to October in Andhra Pradesh which is better suited to rice production. Alternately, there is no planting season for wheat in Andhra Pradesh or Tamil Nadu, the other relatively large producers of rice in southern India. We use information from both autumn and summer rice planting seasons as there may be more than one annual rice harvest in some states; there is only one annual wheat harvest. Interactions of normalized cropped areas and corresponding planting months in states over time are the identifying instruments, as shown in Eq. (2). The key source of identification is the variation in the planting seasons across Indian states: two infants conceived in the same month (but in different states) will be exposed to differing levels of fertilizer agrichemicals because of these staggered planting seasons. The second stage of the IV estimation is similar to Eq. (1) except that $F_{jtm_c}$ and $P_{jtm_c}$ (BOD) are replaced by their predicted orthogonal components from Eq. (2).

[15] Rice and wheat cropped area and information on crop sowing months were obtained from the *Statistical Abstract of India* and *Area and Production of Principal Crops in India*, various years.

In this two stage specification, the identifying assumption required for the effects to be interpreted as causal is that the instruments satisfy the instrument validity conditions: they are correlated with the presence of agrichemicals and BOD in water but, conditional on these variables, they are uncorrelated with child health outcomes. We present numerous tests of instrument validity below; in particular, we show that the timing of conception across months is orthogonal to the identifying instruments, and that the instruments are uncorrelated with characteristics of the planting season that may affect child health outcomes such as the incidence of disease.

## 5. Data

### 5.1. Water data

The water quality data are from the Central Pollution Control Board (CPCB) of India, which, as of 2005, monitors inland water quality at 870 stations under two programs: the Global Environment Monitoring System (GEMS) and Monitoring of Indian National Aquatic Resources (MINARS). The monitoring network covers all rivers and their tributaries, and other sources of water such as creeks, wells, tanks, lakes, ponds, and canals. Although the CPCB has collected water data from 1978 onwards, they maintain electronic records only from 2005. Computable water quality information on CPCB measures was compiled from two other sources: the UNEP GEMS/Water program, which computerized CPCB records from 1978 to 2005 for a subset of monitoring stations; and Greenstone and Hanna (2011) which uses electronic water quality data from 1986 to 2005 for a subset of monitoring stations (489 stations in 424 cities). Remaining gaps were filled in by using information from annual water quality statistics publications obtained from the CPCB. While it is likely that water toxicity levels vary widely over the year, we use the annual average level of each water quality measure to proxy for the missing monthly value for the corresponding state and year (since the annual handbooks do not publish monthly level information) to create our complete monthly-level water quality data which spans 1978–2005. We end at 2005 because that year coincides with the last round of DHS data.

The CPCB collects detailed water quality statistics on a number of measures. These include information on microbiology (fecal coliform), nutrients (nitrates, nitrogen kjeldahl, phosphates), organic matter (BOD), major ions (chloride, magnesium, potassium), metals (arsenic, boron, lead, mercury) and physical/chemical characteristics of water (pH, temperature). As noted above, BOD is included in the models as a control for the general level of water pollution with higher levels of

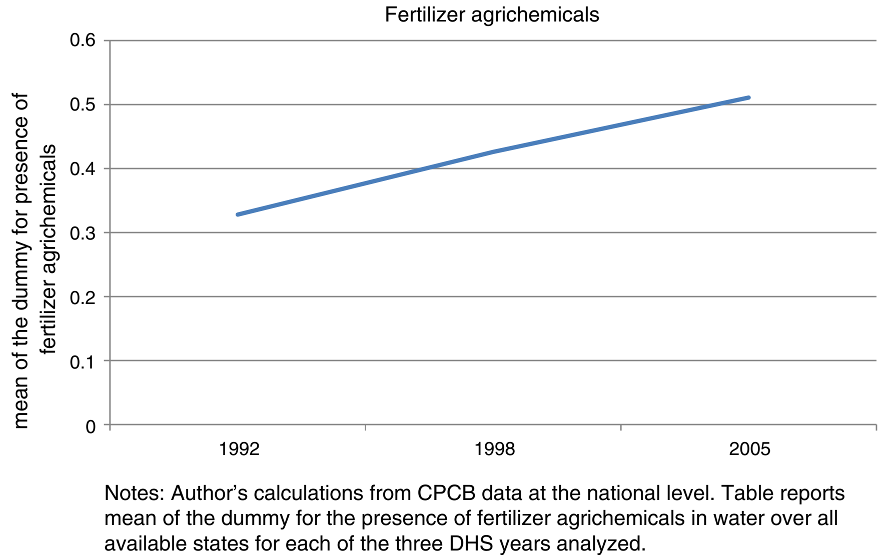


**Fig. 6.** Trend in presence of fertilizer agrichemicals in water over time. Notes: Author's calculations from CPCB data at the national level. Table reports mean of the dummy for the presence of fertilizer agrichemicals in water over all available states for each of the three DHS years analyzed.

BOD indicative of more polluted water. Fig. 5 reports the trend in BOD in our sample. The approximately 28% increase in the level of BOD from 1992 to 2005 shows that industrial and other pollutants have contributed to a serious contamination of water in recent times.

As noted above, since there is no direct measure of the presence of fertilizer agrichemicals in the water data, we create a commensurate variable using information on the main chemical components of fertilizers in India and the EPA's thresholds for drinking water. Fig. 6 shows the trend in the average presence of fertilizer agrichemicals in water. It is apparent that agrichemical levels have risen over time; these data indicate that the presence of agrichemicals in the month of conception increased by about 56% between 1992 and 2005. Table 1 reports average BOD and fertilizer agrichemical levels in the month of conception, demarcated by all areas and wheat and rice growing areas in India. These estimates indicate that although wheat and rice growing areas have some deterioration in water quality in terms of BOD, levels are modest in comparison to the presence of agrichemicals in water in these regions. Next, we discuss our demographic data for India.

### 5.2. Demographic data

Child health outcomes, maternal, paternal and household characteristics are available from three rounds of the Indian National Family Health Survey (NFHS). These are the DHS for India; in addition to the maternal risk factors and demographic characteristics that are asked of all women between the ages of 15 and 49, these data contain detailed reproductive histories on the year and month of delivery of every child born, gender of the child, and information on height-for-age and weight-for-age z scores for children less than age five. For purposes of estimation, these measures are merged with the water quality data on the basis of each child's state of residence and year and month of conception.[16] Year and month of conception are determined retrospectively using information on year and month of birth of the child, assuming a nine month gestation cycle.[17] The resulting data set has child health outcomes matched with agrichemical presence in the month of conception, BOD in the month of conception and other characteristics. Table 1 presents summary statistics of these child-specific, woman-specific, husband-specific, household-specific and state-specific characteristics in our sample, differentiated by crop growing areas.[18] Results are reported for unique observations at each level. Hence for example, while the child-specific variables are reported at the child-level (for children less than or equal to five years of age), women-specific variables are reported for each woman so that the number of births a woman has had does not weight her importance in the summary statistics. Further, although the DHS contain many thousands of child observations in each year, our sample is more limited in number due to missing child characteristics in 1998 and missing values in the BOD variable. These missing values in BOD are not systematic; they arise primarily because of administrative re-structuring at CPCB that led to the elimination of certain branches that monitor water quality.[19]

Table 1 shows that in general, order of birth ranges from 2.6 to 3.3 and 58 to 64% of children are average in size at birth. Women are between 31 and 33 years of age and literacy ranges from 27 to 45%.[20] Work probabilities for women, especially self-employment probabilities, are about the same across growing regions, as is woman's general health as measured by body mass index. Log number of conceptions in a month, which is proxied by the number of live births per month dated retrospectively by nine months, is also comparable across areas.

Husband-specific characteristics are also similar across wheat- and rice-producing areas. Husband's age is about the same as is literacy (measured by a declining proportion of husbands with no education). Household-specific measures indicate that about three quarters of our sample is rural and that this proportion is somewhat higher in wheat growing areas. Male headship is about 93%, about 80% of households

[16] The average woman has lived in her place of residence between seventeen and twenty years in these data. Hence bias from endogenous migration is not likely to be an issue. Ideally, we would have liked to merge on the basis of child's state of birth to control for migration, but this information is not collected in the DHS.

[17] Alternative specifications using a 10 month gestation cycle (40 weeks) had similar results.

[18] Information on per-capita net state domestic product was obtained from the Economic Organization and Public Policy Program (EOPP) database from the London School of Economics. Data on rainfall, malaria cases, tuberculosis (TB) deaths, external deaths, and live births/conceptions were obtained from various years of the *Vital Statistics of India*. Data on air temperature and average elevation were obtained from India Agriculture and Climate Data Set (Dinar et al., 1998). Wheat and rice yields were obtained from the Directorate of Economics and Statistics, Department of Agriculture, various years.

[19] About 1% of observations in BOD are missing in the water quality data. We test that the missing BOD values are not systematically correlated with the instruments in Table 4 below.

[20] About 20% of observations in whether the child was nursed are missing in 1998; we address this below.

**Table 1**
Summary statistics for key variables.

| Variables | All areas | | Wheat areas | | Rice areas | |
|---|---|---|---|---|---|---|
| | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| *Outcomes* | | | | | | |
| Born alive but died before 11 months (infant mort.) | 0.074 | (0.034) | 0.088 | (0.031) | 0.059 | (0.034) |
| Born alive but died in first month (neonatal mort.) | 0.048 | (0.024) | 0.056 | (0.022) | 0.039 | (0.025) |
| Born alive but died b/w 1 and 11 months (post-natal mort.) | 0.026 | (0.017) | 0.032 | (0.016) | 0.020 | (0.016) |
| Height-for-age z score | −1.861 | (1.521) | −2.035 | (1.546) | −1.636 | (1.561) |
| Weight-for-age z score | −1.958 | (1.136) | −2.049 | (1.149) | −1.849 | (1.141) |
| *Water pollutants* | | | | | | |
| Level of biochemical oxygen demand in concep. month | 0.004 | (0.007) | 0.004 | (0.010) | 0.002 | (0.002) |
| Dummy for presence of agrichemicals in concep. month | 0.452 | (0.498) | 0.390 | (0.488) | 0.461 | (0.499) |
| *Child-specific* | | | | | | |
| Order of birth | 2.942 | (1.969) | 3.255 | (2.124) | 2.550 | (1.693) |
| Dummy for child was nursed | 0.947 | (0.225) | 0.960 | (0.195) | 0.929 | (0.257) |
| Male child | 0.513 | (0.500) | 0.501 | (0.500) | 0.510 | (0.500) |
| Dummy for child was large at birth | 0.183 | (0.387) | 0.137 | (0.344) | 0.241 | (0.428) |
| Dummy for child was average at birth | 0.605 | (0.489) | 0.642 | (0.480) | 0.582 | (0.493) |
| Age of child | 2.579 | (1.667) | 2.637 | (1.673) | 2.453 | (1.609) |
| Number of siblings | 2.575 | (2.120) | 3.019 | (2.285) | 1.981 | (1.782) |
| *Women-specific* | | | | | | |
| Women's age | 31.897 | (7.193) | 32.553 | (7.192) | 31.087 | (7.078) |
| Dummy for woman is literate | 0.348 | (0.476) | 0.269 | (0.444) | 0.445 | (0.497) |
| Dummy for woman is currently working | 0.390 | (0.488) | 0.334 | (0.472) | 0.401 | (0.490) |
| Dummy for woman works in farm., fish., hunt. or log. | 0.312 | (0.463) | 0.298 | (0.457) | 0.339 | (0.473) |
| Dummy for woman works for family member | 0.441 | (0.497) | 0.523 | (0.500) | 0.310 | (0.463) |
| Dummy for woman works for someone else | 0.436 | (0.496) | 0.349 | (0.477) | 0.563 | (0.496) |
| Dummy for woman is self-employed | 0.123 | (0.328) | 0.128 | (0.334) | 0.127 | (0.333) |
| Woman's body mass index | 20.229 | (3.680) | 20.102 | (3.481) | 20.440 | (3.861) |
| Dummy for woman consumes fruits daily or weekly | 0.317 | (0.465) | 0.247 | (0.431) | 0.362 | (0.481) |
| Dummy for woman consumes veges. daily or weekly | 0.970 | (0.170) | 0.971 | (0.167) | 0.958 | (0.201) |
| Dummy for woman consumes eggs daily or weekly | 0.278 | (0.448) | 0.145 | (0.352) | 0.513 | (0.500) |
| Dummy for wom. con. chicken/meat/fish daily or weekly | 0.247 | (0.431) | 0.106 | (0.307) | 0.492 | (0.500) |
| Dummy for woman smokes | 0.026 | (0.160) | 0.040 | (0.195) | 0.015 | (0.120) |
| Dummy for woman drinks alcohol | 0.026 | (0.159) | 0.020 | (0.141) | 0.056 | (0.230) |
| Number of living children woman has | 3.590 | (1.759) | 3.973 | (1.839) | 3.005 | (1.511) |
| Number of children five years and under | 1.249 | (1.243) | 1.409 | (1.314) | 1.014 | (1.063) |
| Dummy for had prenatal/antenatal care with doctor | 0.118 | (0.323) | 0.074 | (0.262) | 0.187 | (0.390) |
| Husband's age | 37.962 | (8.816) | 37.974 | (9.104) | 37.925 | (8.460) |
| Dummy for husband has no education | 0.338 | (0.473) | 0.359 | (0.480) | 0.342 | (0.474) |
| Dummy for husband has some or all primary school | 0.195 | (0.396) | 0.171 | (0.377) | 0.244 | (0.430) |
| Dummy for husband has some secondary school | 0.304 | (0.460) | 0.298 | (0.457) | 0.281 | (0.450) |
| Dummy for husband has completed sec. sch. or higher | 0.161 | (0.368) | 0.170 | (0.376) | 0.130 | (0.336) |
| Dummy for husband works outside the home | 0.978 | (0.147) | 0.979 | (0.145) | 0.980 | (0.139) |
| Dummy for husband works in farm., fish., hunt., log. | 0.493 | (0.500) | 0.501 | (0.500) | 0.492 | (0.500) |
| Years lived in place of residence | 18.082 | (13.673) | 16.654 | (10.555) | 20.226 | (16.852) |
| Place of residence: capital, large city or small city | 0.152 | (0.359) | 0.126 | (0.332) | 0.123 | (0.328) |
| Place of residence: town | 0.105 | (0.307) | 0.093 | (0.291) | 0.131 | (0.338) |
| Place of residence: countryside | 0.743 | (0.437) | 0.781 | (0.414) | 0.746 | (0.435) |
| Log number of conceptions in a month | 7.822 | (6.215) | 6.977 | (6.979) | 8.418 | (4.643) |
| *Household-specific* | | | | | | |
| Dummy for rural household | 0.743 | (0.437) | 0.781 | (0.413) | 0.746 | (0.436) |
| Age of household head | 43.517 | (12.767) | 43.986 | (12.978) | 42.570 | (12.461) |
| Dummy for household has male head | 0.936 | (0.244) | 0.932 | (0.252) | 0.928 | (0.259) |
| Dummy for household religion is Hinduism | 0.813 | (0.390) | 0.823 | (0.381) | 0.794 | (0.404) |
| Dummy for household religion is Islam | 0.148 | (0.356) | 0.151 | (0.358) | 0.159 | (0.366) |
| Dummy for household belongs to SC/ST | 0.270 | (0.444) | 0.270 | (0.444) | 0.272 | (0.445) |
| Dummy for household owns a radio/transistor | 0.327 | (0.469) | 0.309 | (0.462) | 0.341 | (0.474) |
| Dummy for household owns a television | 0.327 | (0.469) | 0.281 | (0.450) | 0.339 | (0.473) |
| Dummy for household owns a refrigerator | 0.090 | (0.286) | 0.083 | (0.276) | 0.082 | (0.274) |
| Dummy for household owns a motorcycle | 0.121 | (0.326) | 0.116 | (0.320) | 0.103 | (0.304) |
| Dummy for household owns a car | 0.015 | (0.122) | 0.012 | (0.110) | 0.014 | (0.119) |
| Dummy for household has electricity | 0.569 | (0.495) | 0.467 | (0.499) | 0.615 | (0.487) |
| Source of drinking water: piped water | 0.329 | (0.470) | 0.198 | (0.398) | 0.381 | (0.486) |
| Source of drinking water: ground water | 0.434 | (0.496) | 0.557 | (0.497) | 0.375 | (0.484) |
| Source of drinking water: well water | 0.203 | (0.402) | 0.221 | (0.415) | 0.203 | (0.403) |
| Source of drinking water: surface water | 0.024 | (0.153) | 0.018 | (0.134) | 0.029 | (0.168) |
| Source of drinking water: rain water, tanker truck, etc. | 0.010 | (0.098) | 0.006 | (0.078) | 0.012 | (0.109) |
| Toilet facility: flush toilet | 0.248 | (0.432) | 0.201 | (0.401) | 0.290 | (0.454) |
| Toilet facility: pit toilet/latrine | 0.068 | (0.252) | 0.058 | (0.233) | 0.094 | (0.292) |
| Toilet facility: no facility/bush/field | 0.678 | (0.467) | 0.731 | (0.443) | 0.613 | (0.487) |
| *State-specific* | | | | | | |
| Per capita net state domestic product (base 1980/81) | 2.388 | (1.094) | 2.174 | (1.169) | 2.138 | (0.523) |
| Rainfall in millimeters ($\times 10^{-2}$) | 1.009 | (1.404) | 0.702 | (1.029) | 1.136 | (1.136) |

**Table 1** (*continued*)

| Variables | All areas | | Wheat areas | | Rice areas | |
|---|---|---|---|---|---|---|
| | Mean | Std. dev. | Mean | Std. dev. | Mean | Std. dev. |
| Average air temperature in degrees Celsius | 25.411 | (4.644) | 24.028 | (5.793) | 27.469 | (3.585) |
| Number of malaria/TB deaths norm. by state pop. | 0.001 | (0.002) | 0.001 | (0.001) | 0.001 | (0.002) |
| Average elevation in meters ($\times 10^{-2}$) | 3.482 | (1.152) | 3.753 | (1.450) | 2.624 | (0.568) |

Notes: Author's calculations from CPCB and other data merged with DHS data. Weighted to national levels with weights provided by the DHS. Summary statistics for infant, neonatal and post-natal mortalities are computed for all children who have reached twelve months in age (10,497 obs.), one month in age (12,201 obs.), and those who are less than one month in age and those who have reached twelve months of age (11,046 obs.). Summary statistics for height-for-age and weight-for-age z scores are computed from a sample of children less than or equal to five years of age (10,526 obs., there are some missing observations for height-for-age). BOD is measured in mg/l units. Table reports statistics at the unique level for children (aged five years or lower), women, households, and states.

are Hindu, and 27% belong to the disadvantaged caste group in India (Scheduled Caste/Scheduled Tribes). General infrastructure measures are broadly comparable across areas. Access to electricity ranges from 47% in wheat growing areas to 62% in rice growing areas, and ownership of consumer durables such as refrigerators and motorcycles in particular are approximately equal across areas. Piped water (a relatively safe source) is the origin of drinking water for 38% of rice growing areas but only 20% of wheat areas. State-specific measures indicate that per capita state income is broadly comparable across areas, as is the number of malaria cases and TB deaths normalized by state population.

We turn next to a description of the child outcomes we study. These are reported in Table 1 and include infant mortality (child was born alive but died at or less than eleven months of age), neo-natal mortality (child was born alive but died in the first month of life), and post-natal mortality (child was born alive but died between the first and eleventh month of life). In utero exposure to toxins is believed to have the strongest impact on neo-natal mortality; post-natal mortality is more likely to result from diseases (diarrhea), poor nutrition, child living circumstances/environment or accidents. Standardized measures of stunting (height-for-age z score for children less than five years) and being under-weight (weight-for-age z scores for children less than five years) are also analyzed.[21]

Estimates in Table 1 indicate that infant mortality ranges from 6 to 9% in the sample; neo-natal mortality, ranging from 4 to 6%, is its primary component. The height-for-age z score shows that the average Indian child was close to being stunted (the threshold for stunting is less than 2 standard deviations from the mean), and this is especially true in wheat growing areas. Similarly, the average Indian child scored well below conventionally accepted threshold levels for adequate nutrition in terms of the weight-for-age measure, particularly in wheat areas.

## 6. Results

### 6.1. Two stage least squares

Results from the first stage in Eq. (2) for fertilizer agrichemicals and BOD are reported in Table 2. Since we have information on cropped area under rice in both the *kharif* and summer seasons, we use both variables for estimation purposes as noted above. Table 2 reports that the rice instruments and the wheat instrument are statistically significant in the first column. The rice and wheat instruments have a positive effect on the endogenous variable, which is consistent with our hypothesis that agrichemical levels peak in these states during the application months.

Given the nature of these data, it is likely that the effects of the rice and wheat instruments are contaminated with time and state-level heterogeneity. A way to control for this is to include month and year dummies, state dummies, and interactions of month and state dummies and year and state dummies. This also accounts for omitted variables at these levels whose exclusion may bias results. Note that because the identifying instruments in Eq. (2) are continuous (interactions of state and year-wise normalized cropped areas with crop calendar months indicating planting seasons for rice and wheat across states), they still induce exogenous variation which is not saturated by the additional indicators. The second column of Table 2 shows results with the inclusion of these controls. The instruments remain significant and explain about 26% of the variation in agrichemical presence. The F-statistic on the identifying instruments in the second column of Table 2 is above 10, the rule-of-thumb threshold value for sufficient strength. This is consistent with the corresponding $p$-value which strongly rejects the null hypothesis that the identifying instruments are jointly insignificant. The results in Table 2 indicate that the rice and wheat instruments are significant determinants of the seasonal presence of agrichemicals in water.

The third and fourth columns of Table 2 report first stage results for the general measure of water quality, BOD. The rice and wheat instruments have positive effects in Table 2, but as evident from the third column, only the wheat instrument is a significant determinant of BOD levels. Inclusion of controls for state and time heterogeneity in the fourth column results in the wheat instrument becoming statistically insignificant. As noted above, BOD is influenced by the level of agrichemical nutrients from soil-run off, but also by other sources of water pollution such as industrial waste and inadequate wastewater treatment facilities. In fact, the major point sources of BOD are industries such as paper and pulp processing, printing, and wastewater treatment in textile and fabric industries (Smith, 1989). Since our identifying instruments are primarily agricultural-based, and because agrichemicals form a relatively minor constituent of BOD, the instruments perform less well in predicting BOD levels in our sample. We report tests for weak instruments in the two stage least squares (TSLS) results below.

Our main results from the second stage of the TSLS model are presented in Table 3.[22] Before we discuss these results we note that in order to maintain consistency with the format of the agrichemical and BOD data and to have adequate variation to implement a linear instrumental variables model, non-linear outcomes (infant mortality, neonatal mortality, and post-natal mortality) are averaged to the state, year and month levels (height-for-age and weight-for-age are already in linear form and hence do not require this transformation).[23] Linear TSLS is the preferred econometric method since it has the advantage of reporting tests of instrument validity.

[21] Deaton and Dreze (2009) note that for Indian children, the weight-for-age z score is the preferred measure of under-weight (as opposed to weight-for-height).

[22] Alternate specifications which replace missing values for the nursed indicator in 1998 with the average for that variable (and a dummy to indicate when that variable was missing) led to results that were essentially the same. These are reported in Table 2 of the online appendix.

[23] Appendix Table 1 presents results in which these outcomes are at the individual level. These results are consistent with the main results in Table 3.

**Table 2**
First-stage regressions on identifying instruments.

| | Endogenous variable: average of the dummy for presence of fertilizer agrichemicals in month of conception | | Endogenous variable: log of the level of biochemical oxygen demand in month of conception | |
|---|---|---|---|---|
| Autumn rice crop area × Autumn rice sowing months | 0.834* | 0.881* | 0.445 | 1.095 |
| | (0.452) | (0.503) | (0.493) | (0.689) |
| Summer rice crop area × Summer rice sowing months | 3.636** | 5.038*** | 1.654 | 4.138 |
| | (1.711) | (1.495) | (1.161) | (2.699) |
| Wheat crop area × Wheat sowing months | 0.868*** | 0.698*** | 0.249* | 0.166 |
| | (0.198) | (0.208) | (0.144) | (0.178) |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes | Yes |
| Includes month and year dummies, state dummies, and their interactions | No | Yes | No | Yes |
| R-squared | 0.093 | 0.259 | 0.061 | 0.167 |
| F-statistic | 6.450 | 12.160 | 1.330 | 1.140 |
| | [0.003] | [0.0001] | [0.292] | [0.356] |
| Observations | 12,201 | 12,201 | 12,201 | 12,201 |

Notes: Weighted to national level with weights provided by the DHS. Table reports OLS regressions. Standard errors in parentheses are clustered by state. *p*-Values in square brackets. The notation *** is $p < 0.01$, ** is $p < 0.05$, and * is $p < 0.10$. F-statistics reported are for the identifying instruments. Regressions include a constant term and other characteristics as noted in the table. Restricted to sample with the largest number of observations for child outcomes.

**Table 3**
Instrumental variables effects of fertilizer agrichemicals and BOD on outcomes.

| | Infant mortality | Neo-natal mortality | Post-natal mortality | Height-for-age z score | Weight-for-age z score |
|---|---|---|---|---|---|
| Average of the dummy for the presence of fertilizer chemicals in month of conception | 0.078** | 0.068* | 0.001 | −1.453* | −0.606* |
| | (0.031) | (0.038) | (0.008) | (0.809) | (0.360) |
| Log of the level of biochemical oxygen demand in month of conception | −0.037 | −0.029 | 0.007 | −0.579 | −0.241 |
| | (0.068) | (0.078) | (0.028) | (1.084) | (1.656) |
| Anderson–Rubin Wald test | 21.200 | 13.160 | 0.370 | 11.910 | 7.810 |
| | [0.0001] | [0.004] | [0.946] | [0.008] | [0.050] |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes | Yes | Yes |
| Includes child, woman and husband-specific characteristics, and state-specific characteristics | Yes | Yes | Yes | Yes | Yes |
| Includes month and year dummies, state dummies, and their interactions | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 10,497 | 12,201 | 11,046 | 10,402 | 10,526 |

Notes: Weighted to national level using weights provided by the DHS. Standard errors in parentheses are clustered by state. The notation *** is $p < 0.01$, ** is $p < 0.05$, and * is $p < 0.10$. Regressions are estimated with two stage least squares models. *p*-Values in square brackets. Infant mortality is computed for all children who have reached twelve months of age, neonatal mortality is computed for all children who have reached one month of age, and post-natal mortality includes children who are less than one month of age and those who have reached twelve months of age. Height-for-age and weight-for-age z scores are collected for children less than or equal to five years of age.

Table 3 reports the instrumental variables results for the impact of average fertilizer presence in water in the month of conception on child health outcomes. Sample sizes differ across infant mortality and its components since children who have not reached the age of 11 months, for example, are excluded from the infant and post-natal mortality regressions. Until the child exits the hazard period, it is not possible to know whether he/she will die before the cut-off age. In a similar vein, neonatal mortality includes only those children who have crossed one month of age. Height-for-age and weight-for-age z scores are recorded for all children who are less than five years of age; however, as evident from the table, height-for-age is missing for a small number of children.

We begin by noting that the Anderson–Rubin Wald test that the coefficients on the endogenous regressors are jointly equal to zero (test of weak instruments) is rejected at the 10% level in all but one model of Table 3. The first column reports that fertilizer agrichemicals have a strong positive impact on infant mortality. Estimates indicate that a unit increase in the average measure of such agro-toxins increases average infant mortality by 0.08 units. This means that for a 10% increase in the average level of agrichemicals in water, average infant mortality increases by 4.64%. The second column of Table 3 shows that most of this effect comes from the adverse consequences on neo-natal mortality, as expected. The coefficient in this column indicates that for a 10% increase in the average level of fertilizer in water, average neo-natal mortality increases by 6.22%. Table 3 shows that BOD is not significantly associated with infant or neo-natal mortality.[24]

Table 3 also reports the instrumental variable results for the impact of average fertilizer presence in water in the month of conception on long-run child health outcomes and, as expected, agrichemicals negatively impact height-for-age and weight-for-age z scores. Focusing on the weight-for-age z score which is considered to be a comprehensive measure of child health in India (Deaton and Dreze, 2009), estimates indicate that for a 10% increase in the level of agrichemical toxins in water, weight-for-age z scores as of age five decline by about 0.014 standard deviations. This is a significant but not overly large effect. Even though the magnitude of the effect is modest, it is striking that exposure in the first month has such long-lasting negative effects on child health.[25]

[24] Table 1 in the on-line appendix shows that there is little to no change in the impact of agrichemicals when BOD is excluded from the regressions.

[25] We also tested whether the presence of fertilizer agrichemicals in water affects the likelihood that a child's gender is male (males in utero are reported to be more susceptible to environmental risks than are females — Garry et al., 2002; Sanders and Stoecker, 2011; Drevenstedt et al., 2008). The results were in the hypothesized direction, with gender less likely to be male in the presence of more water toxins, but were statistically insignificant (results available on request).

**Table 4**
Robustness checks for instruments.

| Identifying Instruments | Log of number of accidental deaths | Acc. to pre- or antenatal doctor | Log of the number of conceptions in a month | Rich household | Missing BOD values | Rainfall | Air temperature |
|---|---|---|---|---|---|---|---|
| Autumn rice crop area × Autumn rice sowing months | 0.001 | −0.052 | 9.447 | 0.003 | −0.021 | 0.619 | −0.355 |
| | (0.001) | (0.155) | (8.153) | (0.050) | (0.042) | (1.064) | (0.283) |
| Summer rice crop area × Summer rice sowing months | 0.004 | 0.049 | 22.407 | −0.091 | −0.026 | 0.536 | −1.343*** |
| | (0.003) | (0.289) | (25.268) | (0.089) | (0.128) | (1.491) | (0.392) |
| Wheat crop area × Wheat sowing months | −0.0001 | −0.186 | −1.416 | 0.018 | −0.051 | 1.846*** | −0.916*** |
| | (0.0003) | (0.115) | (2.985) | (0.015) | (0.034) | (0.537) | (0.219) |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Includes child, woman and husband-specific characteristics, and state-specific characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Includes month and year dummies, state dummies, and their interactions | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.718 | 0.336 | 0.693 | 0.143 | 0.034 | 0.719 | 0.971 |
| F-statistic | 0.68 | 1.090 | 0.050 | 2.080 | 1.470 | 5.300 | 13.440 |
| | [0.576] | [0.373] | [0.686] | [0.131] | [0.250] | [0.006] | [0.0004] |
| Number of observations | 8350 | 12,979 | 6743 | 12,979 | 12,979 | 12,979 | 11,574 |

| Identifying instruments | Diseases (malaria, TB) | Mother's education | Father's education | Asset ownership | Rural areas | Number of siblings | Consumption |
|---|---|---|---|---|---|---|---|
| Autumn rice crop area × Autumn rice sowing months | 0.212 | −0.140 | −0.926 | −0.065 | 0.071 | 0.204 | 0.043 |
| | (0.205) | (0.238) | (0.963) | (0.109) | (0.059) | (0.128) | (0.052) |
| Summer rice crop area × Summer rice sowing months | 0.722 | −0.164 | 2.732 | −0.336 | −0.108 | 0.307 | −0.033 |
| | (0.492) | (0.482) | (3.432) | (0.303) | (0.203) | (0.356) | (0.146) |
| Wheat crop area x Wheat sowing months | 0.442 | 0.050 | 2.143 | −0.017 | 0.017 | 0.133 | 0.002 |
| | (0.640) | (0.084) | (1.551) | (0.055) | (0.030) | (0.096) | (0.031) |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Includes child, woman and husband specific characteristics, and state-specific characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Includes month and year dummies, state dummies, and their interactions | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| R-squared | 0.930 | 0.349 | 0.238 | 0.297 | 0.601 | 0.936 | 0.454 |
| F-statistic | 0.890 | 0.320 | 2.600 | 0.610 | 2.120 | 2.210 | 0.340 |
| | [0.469] | [0.812] | [0.077] | [0.612] | [0.125] | [0.114] | [0.795] |
| Number of observations | 8350 | 12,979 | 13,002 | 12,979 | 12,979 | 12,979 | 12,979 |

Notes: Weighted to national level with weights provided by the DHS. Table reports OLS regressions. Standard errors in parentheses are clustered by state. *p*-Values in square brackets. The notation *** is $p < 0.01$, ** is $p < 0.05$, and * is $p < 0.10$. F-statistics reported are for the identifying instruments. Accidental deaths include those from bites/stings, accidental burns, falls, drowning, accidental poisoning, transport and other accidents, suicides and homicides. Rich households are those who own a car. Regressions include a constant term.
Mother's education measures whether the mother is literate, father's education measures whether the father has no schooling. Assets measure ownership of car, refrigerators or motorcycles. Consumption measures consumption of green vegetables, fruits, eggs and meat. Regressions include a constant term.

### 6.2. Ordinary least squares

We end this section by reporting ordinary least squares (OLS) models that treat fertilizer agrichemicals and BOD exogenously. This corresponds to the empirical specification in Eq. (1); the OLS results are reported in Appendix Table 2. As indicated in this table, the signs on the fertilizer agrichemical variable are the same as those on most of the 2SLS estimates in Table 3: infant and neo-natal mortality are positively correlated with the presence of fertilizer agrichemicals, while height-for-age z scores are negatively correlated with fertilizer presence. In all three cases the coefficients are smaller in absolute value than are the corresponding 2SLS estimates (and are statistically insignificant), which is consistent with the attenuation bias that results from classical measurement error. This is not the case for the sign on the weight-for-age z score, which is now positive rather than negative as in Table 3. In general, given that we cannot definitively sign the direction or judge the magnitude of the bias resulting from simultaneity and omitted variables in these specifications, a comparison of OLS and IV estimates is less informative in determining the most significant source(s) of bias.

## 7. Robustness checks

The checks conducted in this section ascertain the robustness of the identifying instruments and demonstrate that they satisfy the exclusion restriction, i.e., that they have no indirect effects on child health measures. Table 4 presents first stage tests that check for correlation of the identifying instruments with the number of accidental deaths, access to prenatal or antenatal care provided by a doctor, log number of conceptions in a month, household income, an indicator for missing BOD observations, rainfall, air temperature, diseases, mother's and father's education, asset ownership, residence in rural or urban areas, number of siblings, and food consumption. Accidental deaths[26] are used as a falsification test: the identifying instruments should not have any effects on deaths not linked to fertilizer agrichemicals or BOD. Access to prenatal or antenatal care is a proxy for investments in infant health. The number of conceptions in a month is a test of selection in that we need to ensure that the timing of conception is not related to the instruments. If households timed conception, then conception could be endogenous to the instruments since the sample of children born during the sowing period when fertilizer is applied would be systematically different as compared to children born at other times of the year. The indicator for missing BOD observations tests that the instruments are independent of missing water quality data. Rainfall and temperature test whether the instruments are

[26] Defined as deaths from bites/stings, accidental burns, falls, drowning, accidental poisoning, transport and other accidents, suicides and homicides.

**Table 5**
Robustness checks for other confounding factors.

| | Infant mortality | | | | | Neo-natal mortality | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Average of the dummy for the presence of fertilizer chemicals in month of conception | 0.075** | 0.077** | 0.035** | 0.075** | 0.075** | 0.067* | 0.061** | 0.037*** | 0.079** | 0.067* |
| | (0.031) | (0.033) | (0.014) | (0.034) | (0.031) | (0.040) | (0.027) | (0.014) | (0.035) | (0.041) |
| Log of the level of biochemical oxygen demand in month of conception | −0.036 | −0.017 | −0.019 | −0.044** | −0.035 | −0.030 | 0.004 | 0.020 | −0.035 | −0.029 |
| | (0.066) | (0.051) | (0.027) | (0.022) | (0.070) | (0.081) | (0.034) | (0.023) | (0.023) | (0.084) |
| Rainfall | 0.002 | | | | | 0.001 | | | | |
| | (0.002) | | | | | (0.002) | | | | |
| Air temperature | | −0.017 | | | | | −0.006 | | | |
| | | (0.011) | | | | | (0.006) | | | |
| Log number of malaria cases and TB deaths | | | −0.007 | | | | | −0.005 | | |
| | | | (0.010) | | | | | (0.011) | | |
| Log of wheat yield | | | | −0.003 | | | | | −0.002 | |
| | | | | (0.005) | | | | | (0.007) | |
| Log of rice yield | | | | −0.001 | | | | | −0.001 | |
| | | | | (0.001) | | | | | (0.001) | |
| Woman is currently working | | | | | 0.001 | | | | | 0.001 |
| | | | | | (0.002) | | | | | (0.002) |
| Woman works in agriculture | | | | | 0.001 | | | | | 0.001 |
| | | | | | (0.001) | | | | | (0.001) |
| Woman works for family member | | | | | −0.001 | | | | | −0.001 |
| | | | | | (0.006) | | | | | (0.006) |
| Woman works for someone else | | | | | −0.002 | | | | | −0.002 |
| | | | | | (0.002) | | | | | (0.002) |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Includes child, woman and husband-spec. characteristics, and state-specific charact. | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Includes month and year dummies, state dummies, and their interactions | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 10,497 | 9302 | 9721 | 9302 | 10,497 | 12,201 | 10,852 | 11,830 | 10,852 | 12,201 |

Notes: Weighted to national level using weights provided by the DHS. Standard errors in parentheses are clustered by state. The notation *** is $p < 0.01$, ** is $p < 0.05$, and * is $p < 0.10$. Regressions are estimated with two stage least squares models. Number of malaria cases and TB deaths are measured by state and year of conception, as are wheat and rice yields. Results for post-natal mortality are not reported in table due to lack of space, these are available on request. Regressions for rice and wheat yields also include average elevation as a control for market integration.

systematically correlated with weather outcomes. We also test for the correlation of instruments with diseases such as malaria and tuberculosis (TB) which may vary by season. Parental education, asset ownership, rural/urban area of residence and number of siblings test whether the instruments predict pre-conception characteristics of households. The food consumption indicator tests whether the instruments are correlated with food shortages that often precede the agricultural sowing months. As evident from Table 4, the rice and wheat instruments have no statistical impact on most outcomes and the F-statistics as well as the corresponding *p*-values confirm this conclusion. The instruments are correlated with rainfall and temperature, but this is to be expected since it is precisely these characteristics that make certain months of the year more suitable for the planting of crops. In Table 5 that follows, we demonstrate that including rainfall and temperature in the second stage has little to no effect on the main results in Table 3, which continue to remain significant.

We continue the discussion of robustness checks by further testing the exclusion restriction. For the identifying instruments to have indirect effects on child health through correlation with potential confounding variables, such variables would have to vary seasonally and by agricultural region in the same way that fertilizer concentrations vary seasonally and across regions. Weather-related natural phenomena such as average rainfall and air temperature, as well as the incidence of diseases such as malaria and TB, may satisfy these conditions, and we verify the validity of our instruments with respect to these variables (Table 4 already showed that the instruments are not correlated with disease). In particular, air temperature may have independent effects on child health measures such as infant mortality conditional on rice and wheat instruments (for example, the likelihood of infant mortality may rise when temperatures are unseasonably warm, as noted in Burgess et al., 2011). The incidence of disease may also vary seasonally and by regions and have indirect effects on child health through influencing mother's health in the year of conception. To account for the effects of air temperature and the incidence of disease, these variables are directly included in the second stage. Furthermore, if a "hungry season" immediately precedes crop sowing cycles, as is usually the case in agriculture, the timing of food shortages may independently impact the mother's health net of the identifying instruments (Table 4 already shows no systematic correlation between the instruments and food consumption). We include retrospective information on wheat and rice yields (tons/ha) in the second stage to adjust for such effects. Average elevation is also included in the second stage to control for market integration which may determine how widely food shortages are experienced at the state level. Finally, if women's labor increases during sowing cycles, this may also invalidate the exclusion restriction. Given the lack of information on hours worked in the DHS data, we include a full set of indicators on the types of work undertaken by women to control for these effects (note that many of these variables are already included in the main specifications discussed above). The results of these tests are reported in Table 5.

It is evident that the inclusion of average rainfall, air temperature, log number of malaria cases and TB deaths, log wheat and rice yields, and controls for woman's work do not change the main results in Table 3. The magnitude of fertilizer agrichemicals in response to the inclusion of the weather variables is about the same in its impact on infant mortality in Table 5 as in Table 3, and still significant. In

**Table 6**
Instrumental variables effects: impact of average of fertilizer agrichemicals and BOD.

| | Infant mortality | Neo-natal mortality | Post-natal mortality | Height-for-age z score | Weight-for-age z score |
|---|---|---|---|---|---|
| *Trimester before conception* | | | | | |
| Average of dummy for presence of fertilizer in the trimester before conception | 0.057 | 0.046 | 0.001 | 0.970 | 0.284 |
| | (0.043) | (0.049) | (0.009) | (1.537) | (0.771) |
| Level of biochemical oxygen demand in the trimester before conception $\times 10^{-2}$ | 0.144 | 0.204 | −0.027 | 0.918 | 6.101 |
| | (0.264) | (0.263) | (0.054) | (5.093) | (6.284) |
| Number of observations | 10,437 | 12,139 | 10,982 | 10,345 | 10,468 |
| *Six months before conception* | | | | | |
| Average of dummy for presence of fertilizer in the six months before conception | 0.085 | 0.062 | 0.005 | 2.716 | 0.806 |
| | (0.065) | (0.052) | (0.009) | (1.682) | (0.805) |
| Level of biochemical oxygen demand in the six months before conception $\times 10^{-2}$ | 0.032 | 0.026* | 0.004 | −0.893 | −0.249 |
| | (0.020) | (0.014) | (0.007) | (0.596) | (0.288) |
| Number of observations | 10,550 | 12,260 | 11,100 | 10,402 | 10,526 |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes | Yes | Yes |
| Includes child, woman and husband-specific characteristics, and state-specific characteristics | Yes | Yes | Yes | Yes | Yes |
| Includes month and year dummies, state dummies, and their interactions | Yes | Yes | Yes | Yes | Yes |

Notes: Weighted to national level using weights provided by the DHS. Standard errors in parentheses are clustered by state. The notation *** is $p < 0.01$, ** is $p < 0.05$, and * is $p < 0.10$. Regressions are estimated with two stage least squares models.

**Table 7**
Disaggregated instrumental variable effects of the presence of fertilizer agrichemicals and BOD in month of conception.

| | Neo-natal mortality | | | | | |
|---|---|---|---|---|---|---|
| | Uneducated women | Educated women | Rural areas | Urban areas | Uneducated husbands | Educated husbands |
| Average of the dummy for the presence of fertilizer chemicals in month of conception | 0.077** | 0.029* | 0.077* | 0.064* | 0.084** | 0.057 |
| | (0.032) | (0.016) | (0.042) | (0.035) | (0.041) | (0.039) |
| Log of the level of biochemical oxygen demand in month of conception | −0.049 | 0.029 | −0.054 | −0.070* | −0.074 | 0.000 |
| | (0.062) | (0.046) | (0.069) | (0.040) | (0.099) | (0.060) |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes | Yes | Yes | Yes |
| Includes child, woman and husband-specific characteristics, and state-specific characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Includes month and year dummies, state dummies, and their interactions | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 7141 | 5060 | 9563 | 2638 | 4168 | 8042 |

Notes: Weighted to national level using weights provided by the DHS. Standard errors in parentheses are clustered by state. The notation *** is $p < 0.01$, ** is $p < 0.05$, and * is $p < 0.10$. Regressions are estimated with two stage least squares models. Uneducated women have no schooling; educated women either have some or all primary school, some secondary school, or have completed secondary school or higher. Uneducated husbands have no schooling; educated husbands include those with some or all primary school, some secondary school, completed secondary school or higher.

terms of neo-natal mortality, agrichemical effects are also comparable and still measured with precision. Inclusion of malaria cases and TB deaths in the second stage decreases the magnitude of the effect of agrichemical toxins in the month of conception on infant mortality and neo-natal mortality (we should note that malaria and TB deaths are missing for 1989, 2003 and 2004; hence the samples are not strictly comparable). The impact of agrichemicals remains evident even with controls for food quantities (rice and wheat yields) and the types of work women engage in. BOD continues to have a mostly insignificant effect in Table 5. These results in Table 5 corroborate the results reported above by demonstrating that the instruments are randomly assigned.[27]

[27] Other checks that were implemented included interacting agrichemicals with sources of drinking water and interacting agrichemicals with the rural dummy. The results were not significantly different from zero. We also checked to see whether gains from access to fertilizer disproportionately affected the rich or middle income — again, there was no evidence that this was the case.

We conclude the Robustness checks section by discussing the results in Table 6 which reports additional falsification tests. In particular, the first panel of Table 6 shows that child health outcomes are not significantly associated with agrichemical or BOD presence in water in the trimester before conception. The second panel of Table 6 extends the time-span to show that there is mostly no effect on child health measures from agrichemicals and BOD in the six months preceding conception (BOD is found to have a marginally significant impact on neo-natal mortality, but that is the only instance). We note however that although the estimates are insignificant, the magnitudes of the coefficients for infant and neo-natal mortality look similar in the second panel of Table 6 and Table 3. But this is not the case for post-natal mortality or height-for-age and weight-for-age z scores, and taken together with the falsification tests in the trimester before conception, the results in Table 6 confirm the robustness of our findings.

## 8. Heterogeneity in impact of agrichemicals

The remaining tables consider different specifications of the main TSLS results in Table 3. Table 7 reports disaggregated regressions for

**Table 8**
Instrumental variable effects: impact of average of fertilizer agrichemicals and BOD in the first to third trimesters.

| | Infant mortality | Neo-natal mortality | Post-natal mortality | Height-for-age z score | Weight-for-age z score |
|---|---|---|---|---|---|
| *First trimester months* | | | | | |
| Average of dummy for presence of fertilizer in the first trimester | 0.082* | 0.075 | 0.005 | −1.831* | −0.563 |
| | (0.046) | (0.049) | (0.010) | (1.093) | (0.612) |
| Level of biochemical oxygen demand in first trimester × $10^{-2}$ | −0.260 | −0.195 | −0.051 | 0.098 | 4.870 |
| | (0.387) | (0.378) | (0.066) | (1.637) | (4.701) |
| Number of observations | 10,437 | 12,139 | 10,982 | 10,345 | 10,468 |
| *Second trimester months* | | | | | |
| Average of dummy for presence of fertilizer in the second trimester | 0.068*** | 0.056 | 0.004 | −1.431 | −1.489 |
| | (0.025) | (0.036) | (0.008) | (0.911) | (1.143) |
| Level of biochemical oxygen demand in second trimester × $10^{-2}$ | −0.018 | 0.040 | 0.018 | 3.793 | 10.495 |
| | (0.144) | (0.178) | (0.089) | (3.269) | (15.329) |
| Number of observations | 10,421 | 12,105 | 10,960 | 10,257 | 10,379 |
| *Third trimester months* | | | | | |
| Average of dummy for presence of fertilizer in the third trimester | 0.070* | 0.062* | 0.001 | 2.812 | 2.266 |
| | (0.040) | (0.034) | (0.007) | (2.757) | (1.986) |
| Level of biochemical oxygen demand in third trimester × $10^{-2}$ | 0.145 | 0.074 | 0.024 | −2.874 | −0.783 |
| | (0.146) | (0.090) | (0.046) | (2.907) | (2.344) |
| Number of observations | 10,400 | 12,074 | 10,937 | 10,215 | 10,338 |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes | Yes | Yes |
| Includes child, woman and husband-specific characteristics, and state-specific characteristics | Yes | Yes | Yes | Yes | Yes |
| Includes month/year dum., state dum. and their int. | Yes | Yes | Yes | Yes | Yes |

Notes: Weighted to national level using weights provided by the DHS. Standard errors in parentheses are clustered by state. The notation *** is $p < 0.01$, ** is $p < 0.05$, and * is $p < 0.10$. Regressions are estimated with two stage least squares models.

neo-natal mortality for the following sub-samples: uneducated versus educated women, rural versus urban areas, and households in which husbands have no schooling versus those in which they have some schooling (some or all primary school, some secondary school, or completed secondary school or higher). The negative consequences of fertilizer toxins are particularly evident among the children of uneducated women; although educated women may also be exposed to agrichemical toxins through drinking water, these results indicate that they are able to engage in behaviors that counteract some of the negative in utero consequences of exposure to tainted water; educated women may be more aware of the benefits of filtration and chlorination, for example. Next, in keeping with increased exposure from agriculture, the harmful impact of agrichemicals on neo-natal mortality is most evident in rural areas. There may be spillovers to urban areas as suggested by the significance of the fertilizer coefficient in column four, but the impact is larger in rural areas. The beneficial impact of BOD on neo-natal mortality in urban areas is likely picking up the positive impact of increased income from economic activity. Finally, using husband's education levels to differentiate between poor and rich households, estimates in Table 7 reveal that it is the poor who are particularly susceptible to the detrimental impacts of agro-contaminants. The results in Table 7 underscore that the negative health implications of fertilizer agrichemicals are strongest among the most disadvantaged, specifically the children of uneducated poor women living in rural India.

To investigate whether exposure beyond the month of conception has added effects on child well-being, the final table reports the child health impacts of first, second, and third trimester exposures to agrichemicals and BOD in water. These results are reported in Table 8; it is clear that although infant mortality is affected by exposure in all trimesters, the largest impact is in the first trimester. Neo-natal mortality is significantly affected by the presence of agrichemicals in water in the third trimester; note however that the corresponding fertilizer coefficients in the first and second trimesters are on the margin of being significant as well. Moreover, the magnitude of the agrichemical variable on infant and neo-natal mortality is only slightly different than its corresponding value in Table 3. Consistent with the results above, there are no significant effects on post-natal mortality. Among the anthropometric indicators, height-for-age is negatively affected by agrichemical exposure, but only in the first trimester. Although anthropometric measures are thought to be most impacted in the third trimester, the negative effect of agrichemicals is evident only in the first trimester in these data. In summary, these results indicate that there is an additional modest effect from prolonged exposure to water toxins, but not for all of the child health measures we examine.

## 9. Conclusion and implications for policy

This analysis seeks to broaden our understanding of the health effects of fertilizer use on a population that is particularly vulnerable to environmental abuses: infants and young children in a developing country. India provides a uniquely favorable environment in which to analyze this effect, given that its particular soil endowment and geography lead to both seasonal and state-level variation in fertilizer agrichemical contamination of ground and surface water. It is this differing timing of the planting seasons across India's states, and the differing seasonal prenatal exposure of infants and children to agrichemicals that results, which we exploit to identify the impact of water contamination on child health.

Our TSLS analysis of the effects of agrichemicals on different measures of child health provides notable results. We find that a 10% increase in the average level of fertilizer chemicals in water in the month of conception increases the likelihood of infant mortality by about 4.6%. Neo-natal mortality is particularly susceptible to agro-contaminants in water as a 10% increase in water toxins from fertilizers is significantly associated with about a 6.2% increase in mortality within the first month. These are relatively large effects, but they are consistent with the findings in Cutler and Miller (2005) and Galiani et al. (2005).[28]

[28] In particular, Cutler and Miller (2005) argue that the adoption of clean water technologies such as filtration and chlorination was responsible for up to 75% of infant mortality reduction in early twentieth century America. Galiani et al. (2005) conclude that privatization of water supply in low-income areas of Argentina reduced the mortality of children under age 5 by an average of between 5 and 8%.

The findings of this research highlight the tension between greater use of fertilizer to increase yields and the negative child health effects that result from such use. In order to reduce harm from agrichemical exposure, it may be necessary to focus on generating only reasonable yield amounts by curtailing the use of synthetic chemical additives. Strategies to reduce the harmful effects of water toxins while still ensuring a sufficient level of output include increasing reliance on organic fertilizers (compost, manure), and adoption of alternative farming techniques that improve soil productivity without the application of inorganic supplements, such as crop-rotation. Implementing programs to raise consciousness and improve the nutrition of mothers who are most exposed may also counteract some of the negative impacts. Finally, early health intervention programs that provide nutrient supplements to low-birth weight babies may be beneficial. These strategies are likely to be costly for cash-strapped developing countries such as India. However, their adoption may be vital to slowing the unintended health consequences of the widespread use of inorganic fertilizers in Indian agriculture.

More broadly, the line of research we pursue in this paper raises a fundamental question regarding one's assessment of the Green Revolution and its contributions to well-being. By significantly increasing agricultural output in developing countries, Green Revolution techniques unquestionably raised living standards and improved the caloric intake and nutrition of millions of people. However, these results indicate that an assessment focusing on only increased agricultural output excluding the cost of environmental contamination is incomplete. The Green Revolution represented a significant change in the agricultural production system: production based on indigenous seeds and organic inputs was, over time, replaced with an agricultural system reliant on hybrid seeds and agrichemicals. The implementation of this system was widespread across the developing world, and policymakers continue to advocate for increased use of agrichemicals by farmers. While we are not the first analysts to document the environmental impact of this fundamental shift in agricultural production, to the best of our knowledge, this paper is one of the first attempts to credibly identify the effect of agrichemicals on child health in a developing country. However, the paper examines only one, relatively short-term impact of Green Revolution technologies on child health in a single country. Much research remains to be done to investigate whether there are any significant, negative long-term consequences for adult health outcomes of the implementation of these techniques, in India as well as in other countries.

## Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.jdeveco.2013.11.004.

## Appendix A

**Table 1**
Instrumental variable effects of fertilizer agrichemicals and BOD on individual-level outcomes.

| | Infant mortality | Neo-natal mortality | Post-natal mortality |
|---|---|---|---|
| Average of the dummy for the presence of fertilizer chemicals in month of conception | 0.075* | 0.116* | −0.041 |
| | (0.043) | (0.061) | (0.043) |
| Log of the level of biochemical oxygen demand in month of conception | −0.039 | −0.107 | 0.069 |
| | (0.137) | (0.159) | (0.097) |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes |
| Includes child, woman and husband-specific characteristics, and state-specific characteristics | Yes | Yes | Yes |
| Includes month and year dummies, state dummies, and their interactions | Yes | Yes | Yes |
| Number of observations | 10,497 | 12,201 | 11,046 |

Notes: Weighted to national level using weights provided by the DHS. Standard errors in parentheses are clustered by state. The notation *** is $p < 0.01$, ** is $p < 0.05$, and * is $p < 0.10$. Regressions are estimated with two stage least squares models. Infant mortality is computed for all children who have reached twelve months of age, neonatal mortality is computed for all children who have reached one month of age, and post-natal mortality includes children who are less than one month of age and those who have reached twelve months of age.

**Table 2**
OLS effects of fertilizer agrichemicals and BOD on outcomes.

| | Infant mortality | Neo-natal mortality | Post-natal mortality | Height-for-age z score | Weight-for-age z score |
|---|---|---|---|---|---|
| Average of the dummy for the presence of fertilizer chemicals in month of conception | 0.002 | 0.002 | −0.00003 | −0.051 | 0.062 |
| | (0.003) | (0.002) | (0.001) | (0.125) | (0.088) |
| Log of the level of biochemical oxygen demand in month of conception | −0.002 | −0.001 | −0.001 | −0.131 | −0.543 |
| | (0.002) | (0.002) | (0.001) | (0.078) | (0.314) |
| Includes measures of crop area and crop sowing months | Yes | Yes | Yes | Yes | Yes |
| Includes child, woman and husband-specific characteristics, and state-specific characteristics | Yes | Yes | Yes | Yes | Yes |
| Includes month and year dummies, state dummies, and their interactions | Yes | Yes | Yes | Yes | Yes |
| Number of observations | 10,497 | 12,201 | 11,046 | 10,402 | 10,526 |

Notes: Weighted to national level using weights provided by the DHS. Standard errors in parentheses are clustered by state. The notation *** is $p < 0.01$, ** is $p < 0.05$, and * is $p < 0.10$. Regressions are estimated with linear models.

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