Unintended Consequences of Sanitation: Negative Externalities on Water Quality and Health in India

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Abstract

Developing countries have increased sanitation investment to reduce diarrheal diseases. However, the positive health effects of latrine construction can be offset by water pollution and negative health effects due to poor treatment of fecal sludge. I estimate these negative externalities of a sanitation policy in India that subsidized the construction of over 100 million latrines. Exploiting geographical variation in soil characteristics and the differential increase in latrine coverage across districts, I find that the policy increases river pollution by 72%. While it reduces diarrheal mortality overall, this positive health effect is two-thirds smaller in areas with lower wastewater treatment capacity.

JEL: I15, O13, Q53, Q56

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1 Introduction

The importance of sanitation as a health issue in developing countries is widely recognized by researchers and policymakers. Poor access to sanitation facilities and the associated practice of open defecation adversely affect child health by increasing the occurrence of diarrheal diseases. Worldwide, according to the WHO/UNICEF data, 688 million people practiced open defecation in 2016, which is estimated to have caused 432,000 deaths in that year (Prüss-Ustün et al., 2019). To address these issues, developing countries such as India and China have provided significant subsidies for the construction of latrines.[1] Their sanitation policies aim to improve child health by reducing open defecation and exposure to fecal matter near human habitation. These direct health benefits of latrine construction are well-documented (Duflo et al., 2015; Hammer and Spears, 2016; Geruso and Spears, 2018; Spears, 2018; Cameron et al., 2019, 2021).

But little is known about the unintended negative externalities of latrine construction due to poor treatment of fecal sludge, which can offset the direct health benefits. The constructed latrines accumulate a large volume of fecal sludge, which must be emptied periodically by vacuum trucks or by hand. The emptied fecal sludge should then be treated by wastewater treatment plants to disinfect the remaining active pathogens. However, due to insufficient infrastructure, the emptied fecal sludge is instead, in many cases, dumped into rivers, thus polluting the rivers. This water pollution may decrease the overall effectiveness of latrine construction in improving human health. In the extreme, latrine construction can, in fact, worsen health outcomes if water pollution externalities offset any direct positive effects from reduced open defecation.

I therefore examine such negative externalities of latrine construction on water quality and health in the context of India's nationwide sanitation policy, the Swachh Bharat Mission (SBM). Since its inception in 2014, the SBM has allocated about 6 billion US dollars to subsidize the construction of over 100 million latrines at the household level in rural India.[2] As the largest sanitation policy in the world, the SBM's impacts deserve careful examination. I use administrative datasets on the district-level number of latrines from 2012 to 2019 under the SBM and the water quality of about 1,200 monitoring stations along rivers in 337 districts over 10 years to examine the negative externality on water quality. I combine these with district-level diarrheal mortality estimates to examine the effect on health.

[1] Like the Indian government's Swachh Bharat Mission examined in this paper, the Chinese government's "Toilet Revolution" built and upgraded over 10 million rural toilets in 2018 to increase sanitary toilets with sealed and covered septic tanks.

[2] The most commonly constructed latrines in rural India are pit latrines, which are not connected to sewer pipes and accumulate fecal sludge. Emptied fecal sludge can cause water pollution externalities.

Because water pollution externalities can be caused by open defecation practiced before the latrine construction, I analyze the differential effects of latrine construction relative to open defecation. Open defecation generates small amounts of stool in a wide range of locations, which will be flushed into rivers only if it rains and if open defecation sites are close to rivers. On the other hand, latrines concentrate a large volume of fecal sludge that may be dumped directly into rivers. Thus, the volume of fecal sludge that reaches rivers may be larger in the case of latrines than in the case of open defecation.

To identify the causal effects of latrine construction under the SBM on water quality and health, I use two identification strategies. First, I adopt an instrumental variable (IV) design that uses geographical variation in Available Water Capacity (AWC), a proxy for the soil infiltration rate, as an instrument for the number of latrines.[3] Higher infiltration rates increase the risk of groundwater contamination from the fecal sludge accumulated in latrines. Thus, an official technical guideline requires either greater distances between latrines and wells or the addition of impervious materials inside latrines in areas with high infiltration rates, which increases the difficulty and cost of latrine construction. Indeed, I find that lower AWC (higher infiltrate rate) is associated with a smaller increase in latrines in the first stage.

Second, I complement the IV design with a difference-in-differences (DID) design to examine the dynamic evolution of the effects on water quality. In this design, I use baseline latrine coverage as a continuous treatment measure. All districts had, according to the SBM database, achieved almost universal latrine coverage by the target date of 2019, regardless of their baseline latrine coverage.[4] Therefore, districts with lower baseline latrine coverage have experienced a larger increase in latrine coverage, which may lead to a larger increase in water pollution.

My results show that latrine construction under the SBM degrades river water quality while improving health overall. I find that one additional latrine per square kilometer increases fecal coliform in rivers by 3% in the IV design. The total effect of the SBM is estimated to be a 72% increase in river pollution. This negative externality on water quality is similarly found in the DID design. However, one additional latrine per square kilometer reduces the diarrheal post-neonatal mortality per 1,000 people by about 0.029, which is a 1.3% reduction in the IV design. The total effect of the SBM is a 36% decrease in diarrheal mortality. This positive overall health effect suggests that the direct positive health effect outweighs the negative externality on health due to water pollution.

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[3] Soil infiltration rate is the velocity or speed at which water enters the soil. Conversely, AWC is the amount of water that a soil can store that is available for use by plants.

[4] Although there are some debates over whether the universal latrine coverage has actually been achieved under the SBM, a recent survey found that 85% of the rural population used toilets in 2019-2020 (DDWS, 2020).

To explore the mechanism behind these negative externalities, I examine differential effects by the level of complementary investment in the treatment of fecal sludge. Sufficient infrastructure to treat fecal sludge can prevent the dumping of fecal sludge and resulting negative externalities. The most common such infrastructure takes the form of sewage treatment plants (STPs), which co-treat both urban sewer and rural fecal sludge in India. Thus, I compare the effects between areas with higher and lower treatment capacities of STPs than the median in the pre-SBM period. I find that the negative externality on water quality is eliminated in areas with higher treatment capacities in both IV and DID designs.[5] Conversely, the negative externality on water quality is substantial in areas with lower treatment capacities. The negative externality in these areas has become substantial two years after the start of SBM, and this effect has become larger over time, according to the DID design.

This heterogeneity suggests that the health effects of the SBM depend on the treatment capacity of fecal sludge. I find that the total effect of the SBM is a 26% decrease in diarrheal mortality in states with lower treatment capacities, about two-thirds less than the 71% decrease in states with higher treatment capacities in the IV design. This smaller positive health effect in areas with lower treatment capacities suggests that the SBM has a negative externality on health through the water pollution channel. Moreover, the negative externality on health is disproportionally borne by people who are more highly exposed to river pollution. Specifically, I find a smaller positive effect on diarrheal mortality in districts where a higher proportion of people live near rivers in the IV design.

These negative externalities may spill over to downstream districts because dumped fecal sludge can flow downstream along rivers. I test these spillover effects in the modified IV design, where I estimate the effects of upstream latrine construction on downstream outcomes by instrumenting the upstream latrine construction with upstream AWC. I find that upstream latrine construction increase downstream river pollution, especially when upstream areas have lower treatment capacities. Upstream latrine construction decreases downstream diarrheal mortality overall because the positive health effect that comes from the corresponding increase in downstream latrine construction outweighs the water pollution externalities. However, I find that the positive health effect is eliminated in the case of lower treatment capacities, which suggests a large negative externality on health due to water pollution.

A variety of tests corroborate my findings on the negative externalities of latrine construction. First, in an indirect test of the exclusion restriction, I find that AWC has no effects on outcomes prior to the SBM policy (before the technical guideline on infiltration

[5] This null result in areas with higher treatment capacities suggests a low probability that other channels, e.g., the seepage of fecal matter directly from latrines into rivers, affect water quality.

rates was published). Second, in a falsification test, I do not find effects on unrelated water quality indicators and malaria mortality. Third, my results are robust to the consideration of spillovers from neighboring districts, influence from urban areas, and balanced panel.

This paper makes three contributions. First, I contribute to the literature on the effects of sanitation interventions by revealing the negative externalities of latrine construction on the environment and health. Previous studies focused on the direct positive effects of sanitation interventions on child health and mortality (Clasen et al., 2014; Patil et al., 2014; Duflo et al., 2015; Hammer and Spears, 2016; Geruso and Spears, 2018; Spears, 2018; Alsan and Goldin, 2019; Cameron et al., 2019, 2021; Flynn and Marcus, 2021).[6] I complement these findings by showing that latrine construction additionally causes unintended water pollution and negative health effects, which offset the direct positive effects. Moreover, this paper provides new evidence on the environmental and health effects of the SBM policy, which is the world's largest program of latrine construction.

Second, I contribute to the literature on the causes and effects of water pollution by providing the first causal estimates of the environmental effects of latrine construction on river water quality.[7] Previous literature has studied how water quality is affected by water quality regulations (Greenstone and Hanna, 2014; Keiser and Shapiro, 2019) and political boundaries (Kahn et al., 2015; Lipscomb and Mobarak, 2016; Motohashi and Toya, 2022). Another set of studies has investigated the effects of industrial and agricultural wastewater on digestive cancer (Ebenstein, 2012), infant mortality (Brainerd and Menon, 2014; Do et al., 2018), and birth outcomes (Dias et al., 2019). This paper shows that latrine construction substantially increases river pollution (by 72% in the case of the SBM, which is larger than most past studies' estimates), and that this increased water pollution offsets positive health effects on the rate of diarrheal mortality.

Third, more broadly, this paper advances the literature on the unintended negative effects of health policies in developing countries by showing that these negative effects can be minimized with sufficient complementary investment. Past literature documented how health policies unintentionally worsen health outcomes due to the reduction in complementary

[6] Past literature also showed the positive effects of such interventions on educational outcomes (Spears and Lamba, 2016; Adukia, 2017; Orgill-Meyer and Pattanayak, 2020), labor supply (Wang and Shen, 2022), and violence against women (Hossain et al., 2022). Another strand of literature examined the constraints behind latrine adoption, including financial constraints, inadequate information concerning the benefits of latrines and costs of open defecation (Pattanayak et al., 2009; Gertler et al., 2015; Guiteras et al., 2015; Yishay et al., 2017; Lipscomb and Schechter, 2018; Orgill-Meyer et al., 2019), and religious and caste beliefs that discourage latrine use (Spears and Thorat, 2019; Adukia et al., 2021).

[7] Public health literature has examined the association between pit latrines and groundwater quality based on a limited sample of a few hundred latrines (Graham and Polizzotto (2013) reviewed these studies). This paper estimates the causal effects of latrines on river water quality based on nationwide administrative data.

health behaviors (Bennett, 2012; Jeuland et al., 2021), switching to alternative unsafe water sources (Buchmann et al., 2019), and abandonment of and delays in project completion (Bancalari, 2020). This paper shows the unintended negative effect of latrine construction through the displacement of pollution sources from open defecation sites to rivers, an effect that can be eliminated with sufficient investment in the treatment of fecal sludge.

The rest of the paper is organized as follows. Section 2 describes the SBM and its potential effects on water quality and health. Section 3 lays out a simple conceptual framework to guide the subsequent empirical analysis. Sections 4 and 5 describe the data and empirical strategies. Section 6 presents the baseline results of the effects on water quality and health. Section 7 presents the heterogeneous effects of latrine construction. Section 8 concludes.

2 Background

2.1 Latrine Construction under Swachh Bharat Mission in India

In India, a large number of people have historically practiced open defecation due to inadequate access to latrines. For example, about 470 million people in India practiced open defecation in 2013, according to the WHO/UNICEF Joint Monitoring Programme. As such, India has the highest number of people practicing open defecation in the world, more than 10 times that of the country with the second-highest number, Nigeria (Appendix Figure A1).

To eliminate open defecation, the Indian government has implemented four consecutive policies at the central government level.[8] The most recent policy, called the Swachh Bharat Mission (SBM), started in 2014 under the administration of Prime Minister Modi. The SBM set the ambitious goal of achieving universal latrine coverage by October 2nd, 2019, the 150th anniversary of Mahatma Gandhi's birth. The SBM significantly increased the amount of subsidy to about 150 US dollars (12,000 INR) per household. This subsidy covers most of the initial cost of basic pit latrines, the type most widely adopted in rural India.

With this big push to construct latrines, the SBM has used about 6 billion US dollars to build over 100 million latrines in rural India.[9] Latrine coverage dramatically increased from 39.2% in 2013 to 100% in 2019, according to the administrative database of the SBM (Figure 1). A recent government-commissioned survey also found that 85% of the rural population

[8] Although state governments have primary responsibility for public health and sanitation, these central government-level policies were meant to influence the state-level sanitation policies through policy guidance and budget allocation.

[9] According to the actual expenditure shown in the annual budgets of the Indian government, the central government has spent about 6.37 billion US dollars (497 billion INR) from 2014 to 2019. The data source on the number of built latrines is the SBM website (`https://swachhbharatmission.gov.in/SBMCMS/about-us.htm`).

used toilets in 2019-2020, which suggests almost universal latrine coverage had been achieved under the SBM (DDWS, 2020). As the largest sanitation policy in the world, the SBM's impacts on water quality and health deserve careful examination.

2.2 Negative Externality of Latrine Construction on Water Quality

The large-scale latrine construction under the SBM may cause a negative externality on river water quality due to poor treatment of fecal sludge emptied from latrines. Latrines accumulate a large volume of fecal sludge, which must be emptied either by vacuum trucks or manually. The emptied fecal sludge should then be transported to and treated at the wastewater treatment plants to disinfect the remaining active pathogens.[10] However, due to insufficient infrastructure, the emptied fecal sludge is instead frequently dumped into rivers, which can cause water pollution in rivers.[11]

I analyze the differential effects of latrine construction compared to open defecation on water quality. A negative externality on water quality can also be caused by open defecation, which was practiced before the latrine construction. Open defecation generates small amounts of stool in a wide range of locations. Some of these stools decompose in sunlight and will be flushed into rivers only if it rains and if open defecation sites are close to rivers. On the other hand, latrines accumulate a large volume of fecal sludge that may be emptied and dumped directly into rivers. Thus, the volume of fecal sludge that reaches rivers may be larger in the case of latrines than in the case of open defecation.

2.3 Negative Externality of Latrine Construction on Health

The SBM may also result in a negative externality on health through the unintended consequence of increasing river pollution. Exposure to polluted water increases the risks of diarrheal diseases and mortality for people who uses river water in their daily lives.

Latrine construction has direct positive effects on health by reducing open defecation and exposure to fecal matter near human habitation, while at the same time, latrine construction may indirectly cause negative effects on health due to exposure to river pollution. The magnitudes of both the direct positive health effect and the indirect negative externality determine the sign of the overall health effect. This paper empirically investigates this overall health effect in terms of diarrheal mortality.

[10] Although the fecal sludge contained in pits degrades to some degree with time, pathogens can be present even after long-term storage. The primary objective of pit latrines is fecal containment rather than pathogen reduction (Orner et al., 2018).

[11] An ethnographic study on 32 truck operators that clean latrines showed that these operators practice illegal dumping, although this study focuses on urban areas in Bangalore, Karnataka (Prasad and Ray, 2019). Illegal dumping and associated water pollution have also been pointed out by news media.

2.4 Complementary Investment in Treatment of Fecal Sludge

The magnitude of negative externalities on water quality and health varies by the level of complementary investment in the treatment of fecal sludge. The adequate treatment of emptied fecal sludge prevents the dumping of fecal sludge, thus minimizing the negative externalities. Local governments are tasked with developing infrastructure that treats emptied fecal sludge, i.e., sewage treatment plants (STPs) and fecal sludge treatment plants (FSTPs). STPs are large-scale facilities that have been available in India for a long time. India had about 500 STPs in operation in 2015 (CPCB, 2015). STPs are typically designed to treat urban sewage, but they are also increasingly used to co-treat fecal sludge due to the under-utilization of STP capacities in India.[12] On the other hand, FSTPs are newly developed small-scale facilities for treating fecal sludge. FSTPs started operating in 2014, and there were only about only 30 FSTPs in operation at the end of 2019 (Rao et al., 2020).

I use geographical variation in STP capacity in the pre-SBM period to examine the heterogeneous effects on water quality and health.[13] The negative externality on water quality is expected to be substantial in areas with lower treatment capacities. Thus, in these areas, the negative externality on health is also expected to be larger, which suggests a smaller overall positive health effect. Conversely, I expect to find smaller negative externalities in areas with high treatment capacities. In the following sections, I first construct a conceptual framework to derive these predictions and then test them in empirical analysis.

3 Conceptual Framework on Negative Externalities of Latrine Construction

I present a simple conceptual framework to show how latrine construction under the SBM causes negative externalities that offset direct health benefits. A decrease in a latrine price under the subsidy increases the number of constructed latrines, which increases the marginal damage (negative externalities), which offsets the marginal benefit (health benefits). The magnitude of these negative externalities depends on the treatment capacity of fecal sludge.

I consider a district that has N households which can decide whether or not to construct latrines. I suppose that a given household can build a latrine by paying a fixed price (p_{pre}).[14]

[12] Although the data on the actual prevalence of co-treatment is not available, case studies are available for STPs in Panaji (Goa), Kanpur (Uttar Pradesh), and Chennai (Tamil Nadu). Also, policies and guidelines mentioning the co-treatments at STPs are available in multiple states, such as Punjab, Madhya Pradesh, Jharkhand, and Rajasthan (Gupta et al., 2018).

[13] I use STP capacities in the pre-SBM period in 2013 to address the concern of endogenous construction of infrastructure due to increased water pollution. I do not consider FSTP capacities because there were no FSTPs in the pre-SBM period.

[14] The latrine price can include both the initial construction cost of a latrine and the present value of

I denote the maximum number of latrines that can be built in this district as $Q^{max} = N$.

The fecal sludge emptied from latrines in this district is treated by sewage treatment plants (STPs). I give the treatment capacity of fecal sludge as $Q^{stp} \in [0, Q^{max}]$ where Q^{stp} can be interpreted as the number of latrines whose fecal sludge can be treated by STPs. Thus, when the number of latrines (Q) exceeds Q^{stp}, the fecal sludge of $Q - Q^{stp}$ is dumped into rivers, which causes negative externalities on water quality and health. In this conceptual framework, I analyze two cases: (i) low treatment capacity ($Q^{stp} \leq \frac{Q^{max}}{2}$) and (ii) high treatment capacity ($Q^{stp} > \frac{Q^{max}}{2}$).

Figure 2 shows the marginal benefit (MB), marginal cost (MC), and social marginal cost (SMC) of latrine construction for low treatment capacity case (Panel A) and high treatment capacity case (Panel B).

Both panels show the same MB and MC curves. The MB curve represents direct health benefits that come from reduced open defecation and exposure to fecal matter near human habitation.[15] This curve is downward-sloping because some households benefit more than other households — for instance, if they have more infants who are vulnerable to diarrhea. As for MC, the pre-SBM curves are constant at the constant price of latrines ($MC_{pre} = p_{pre}$). The MC curves are shifted down by subsidy under the SBM. Households receive a subsidy of about 150 US dollars for latrine construction, so the post-SBM effective price of latrines ($MC_{post} = p_{post}$) becomes significantly lower than p_{pre}.

The main difference between Panels A and B is SMC. If the treatment capacity is low (Panel A), marginal damage (MD), i.e., the negative externality on health due to river pollution, becomes non-zero, starting from the lower number of latrines. On the other hand, if the treatment capacity is high (Panel B), the MD occurs only at a larger number of latrines. The SMC curves reflect the differences in MD curves because $SMC = MC + MD$.

Based on this conceptual framework, I examine the welfare effects of the SBM in Figure 2. If the treatment capacity is low (Panel A), pre-SBM market equilibrium quantity is Q^e_{pre} at the intersection of MB and MC_{pre}, and pre-SBM optimal quantity is Q^*_{pre} at the intersection of MB and SMC_{pre}. The wedge between Q^e_{pre} and Q^*_{pre}, caused by MD (negative externality), generates deadweight loss (DWL_{pre}). Then, the effect of the SBM is to decrease the marginal cost from MC_{pre} to MC_{post} through subsidy. Thus, the number of latrines increases significantly from Q^e_{pre} to Q^e_{post}. This increase in latrines causes a large increase in negative externality due to low treatment capacity. Deadweight loss significantly increases from DWL_{pre} to DWL_{post}. On the other hand, if the treatment capacity is high (Panel B),

marginal costs for emptying fecal sludge periodically.

[15] In this conceptual framework, MB is assumed to only represent direct health benefits, i.e., reduction in the risks of diarrhea and diarrheal mortality, although there could be other benefits, including an improvement in educational outcomes and reduction in violence against women.

the increase in deadweight loss due to the SBM is limited because the negative externality only occurs at a large number of latrines. The comparison of Panels A and B suggests that subsidies under the SBM adversely impact welfare more significantly in the case of low treatment capacity.

Moreover, I examine the effects of the SBM on water quality and health in Figure 3, which is based on the welfare analysis in Figure 2. In Figure 3, the total benefit represents the total direct health effects, while the total damage represents the total negative externality on health due to water pollution.[16] The difference in the total benefit and total damage (net benefit) is examined as a health outcome in the empirical analysis.[17] The total damage can be interpreted as a degree of water pollution, which corresponds to the water quality outcome in the empirical analysis.

The subsequent empirical analysis estimates the effects of the increase in the number of latrines at market equilibrium from Q^e_{pre} to Q^e_{post} on water quality and health under the SBM. As shown in Figure 3, there are three testable hypotheses in the empirical analysis. The first hypothesis is tested in Section 6, and the second and third hypotheses are tested in Section 7.

1. In general, the SBM improves health overall (increase in net benefit) and increases water pollution (increase in total damage) regardless of treatment capacity.
2. The magnitude of health effects is smaller in the case of low treatment capacity.
3. The magnitude of water pollution is larger in the case of low treatment capacity.

4 Data

I combine administrative datasets on the water quality of rivers and latrines across India to examine the negative externality of latrine construction on water quality. I use district-level diarrheal mortality estimates as an additional outcome to examine the negative externality on health. In the IV design, I use Available Water Capacity (AWC) as an instrument for latrines. I also control for other district characteristics that might affect latrine construction and outcomes. All of these data are spatially matched based on the 2011 district-level boundary data.

[16] The total benefit in Figure 3 is the area under the MB curves of Figure 2. The total damage in Figure 3 is the area bounded by the SMC and MC curves of Figure 2.

[17] I assume that the total benefit is larger than the total damage. In this case, the net benefit is positive, which means that latrine construction improves health overall. This is consistent with the empirical results of this paper.

4.1 Water Quality

This paper adopts two outcome variables: water quality and health. As a first outcome, I use detailed water quality data from 1,189 monitoring stations along rivers in India from 2007 to 2019 (Figure 4). The data is based on the National Water Quality Monitoring Programme (NWMP), managed by the Central Pollution Control Board (CPCB).[18]

Although multiple water quality indicators are available in the NWMP dataset, I use fecal coliform as a main indicator because fecal coliform is a direct measurement of the fecal contamination caused by the fecal sludge emptied from latrines.[19] A higher value of fecal coliform means a higher level of fecal contamination. In the analysis, I use the average of maximum and minimum values of fecal coliform because mean values are only available up to 2014.[20] Lastly, since the distribution of fecal coliform is approximately log normal, we use the log of fecal coliform as a water quality outcome in the analysis.

4.2 Health

Another outcome variable is health. I use the diarrheal mortality estimates (per 1,000 people) from 2000 to 2019, provided as 5-kilometer raster data by the Institute for Health Metrics and Evaluation (IHME, 2020b). This dataset includes estimates of diarrheal mortality of five age groups, i.e., early-neonatal (0-6 days), late-neonatal (7-27 days), post-neonatal (28 days - 1 year), ages 1-4, and under age 5. These estimates are constructed based on the datasets of multiple household surveys, including the India Demographic and Health Survey, the India District Level Household Survey, and the India Human Development Survey. For the analysis, I compute the district-level mean of these estimates based on this raster data and district boundary data.

4.3 Latrines

The treatment variable is the number of latrines. I use the administrative data on the district-level number of household latrines from 2012 to 2019 in rural India, which are scraped from the database available on the SBM website. Based on this dataset, I compute the number of latrines per square kilometer for the IV design. Moreover, I compute the 2013 latrine

[18] I additionally identify the basin of each monitoring station by using the GPS coordinates of monitoring stations and the "Watershed Map of India" of the ML Infomap.

[19] I do not use other common water quality indicators such as Biological Oxygen Demand (BOD) and Dissolved Oxygen (DO) because they capture the overall level of water contamination from various pollution sources, including agricultural and industrial wastewater.

[20] The correlation between mean values and average values of fecal coliform is 0.9973, which suggests that average values are good proxies of mean values.

coverage by dividing the number of household latrines in 2013 by the total number of recorded households in each district for the DID design.[21]

One concern about this dataset is that the number of latrines may be systematically overestimated because the data are collected by the Indian government under the SBM policy, whose aim is to achieve universal latrine coverage. I deal with this potential measurement error by adopting an IV design. Furthermore, it should be noted that the DID design, relying on the variation in baseline latrine coverages, could yield lower-bound estimates because actual latrine coverages could be lower than those in the administrative data.

4.4 Available Water Capacity

In the IV design, I use Available Water Capacity (AWC) as an instrument for the number of latrines. AWC is the amount of water that a soil can store that is available for use by plants, which represents a soil infiltration rate. Higher AWC is associated with a lower soil infiltration rate. The AWC data is available in the Harmonized World Soil Database v1.2 provided by the Food and Agriculture Organization of the United Nations (FAO). This database provides 30 arc-second raster data of AWC across the globe. I compute the district-level mean of AWC based on this raster data and district boundary data.

4.5 Other District Characteristics

I supplement the above information with further data to account for district characteristics that might affect water quality and health. First, I use 0.25-degree raster data of precipitation from 2007 to 2019, provided by the India Meteorological Department (Pai et al., 2014). I aggregate daily raw data into annual data. Then, I construct the district-level mean of precipitation based on this raster data and district boundary data.

Second, I use 15 arc second (<500m at the Equator) raster data of nighttime light to account for the size of the economy at the district level. Specifically, I use the V.2 annual composites of Visible and Infrared Imaging Suite (VIIRS) Day Night Band (Elvidge et al., 2021).[22] I compute the district-level mean of nighttime luminosity in the pre-SBM period based on the annual composite of 2013.

Lastly, I use data on district-level socio-demographic characteristics, including population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates in rural India, in the 2011 Census of India.

[21] I do not consider whether constructed latrines are used due to a lack of district-level panel data on latrine usage. Because the usage rate of constructed latrines can be lower than 100% in India, my estimates represent the lower bound of the effect of the increase in latrine usage.

[22] I use the values of masked average radiance that represents stable lights from which background noises, biomass burning, and aurora are removed.

4.6 Data Matching and Sample Construction

To match water quality data with latrine data, I first use the 2011 district-level boundary data of the ML Infomap and the GPS coordinates of monitoring stations to identify the districts where monitoring stations are located. Then, I match both datasets based on district names.[23] All other data are similarly matched to water quality and latrine data by following the 2011 district boundary.

After the data matching, I construct an unbalanced panel data of 1,189 water quality monitoring stations in 337 districts from 2007 to 2019.[24] In the IV design, I use data of 1,189 stations from 2012 because latrine data is only available from that year. In the DID specification, which relies only on latrine coverage in 2013 as a treatment, I use longer panel data of the same stations from 2007 to 2019. When I examine the health effects, I focus on the same 337 districts used in the analysis of water quality. Specifically, I construct a balanced panel of 337 districts from 2012 to 2019.

Table 1 shows the summary statistics of all variables used in the analysis. Time-varying variables are shown separately for both pre-SBM and post-SBM periods.

5 Empirical Strategy

I empirically examine the effects of latrine construction under the SBM on river water quality and health. Estimates of ordinary least squares (OLS) might be biased due to reverse causality and omitted variables. For example, increased water pollution may impede latrine construction to prevent further water pollution, leading to reverse causality. Moreover, spurious correlations may be caused by unobservables that affect both latrine construction and water quality. For example, unobserved persistent belief on open defecation may reduce the probability of latrine construction and affect water quality due to the associated practice of open defecation.

Therefore, I use two identification strategies to estimate causal effects. First, I adopt an IV design, which uses geographical variation in AWC, a proxy for the soil infiltration rate, as an instrument for the number of latrines. Second, I complement the IV design with the DID design to examine the dynamic evolution of the effects, where I use a differential increase in latrine coverage across districts with different levels of baseline coverage. In both designs, I

[23] I deal with the changes in the district boundary by ensuring that all data are organized according to the 2011 boundary. Latrine data based on the 2019 boundary are aggregated to follow the 2011 boundary by considering the district splits from 2011 to 2019.

[24] In the main specification, I use an unbalanced panel data of water quality to cover as many districts as possible to enhance the external validity. As a robustness check, I run the same analysis on a balanced panel in Section 6.4.

include monitoring station fixed effects in the case of water quality and district fixed effects in the case of health to control for time-invariant unobservables.

5.1 Instrumental Variable Design

In the IV design, I use geographical variation in soil infiltration rates, represented by AWC, which affects the cost and difficulty of latrine construction. The soil infiltration rates determine the pollution risk of groundwater when constructing pit latrines, the most widely adopted type in rural India. Pit latrines consist of a hole, called a pit, that accumulates fecal sludge without a completely sealed wall. Thus, pathogens inside the fecal sludge can percolate into soils, potentially causing fecal contamination of groundwater sources such as wells.[25] The degree of this fecal contamination depends on the soil infiltration rates.

To prevent groundwater pollution, households living in areas with high soil infiltration rates are required to take additional measures when constructing latrines according to the official technical guideline (CPHEEO, 2013). If the effective size (ES) of the soil is 0.2 mm or less, i.e., a lower infiltration rate (higher AWC), pits can be located at a minimum distance of 3 meters from water sources such as wells. However, for coarser soils with ES greater than 0.2 mm, i.e., a higher infiltration rate (lower AWC), the minimum distance must be greater than 3 meters. In cases where the requirement for minimum distance cannot be met, additional investments are mandated for latrine construction. Specifically, the bottom of the pits must be sealed off with impervious materials such as puddle clay and plastic sheeting, and a 500 mm thick envelope of fine sand of 0.2 mm effective size must surround the pit. In short, a higher infiltration rate makes it more difficult to find the space for latrines or increases the cost of their construction due to these additional investments.[26]

Therefore, I use soil infiltration rate, represented by AWC, as an instrument for the number of latrines. Figure 5 shows substantial variation in AWC across districts in India. In the first stage, an area with lower AWC, i.e., a higher infiltration rate, is expected to experience a smaller increase in the number of latrines. As expected, Column 2 of Tables 2 and 3 show that one mm/m decrease in AWC is associated with a decrease in the number of latrines per square kilometer by 0.283 and 0.244, respectively. The F-statistics of the first stage regressions are relatively high (29.954 and 33.374).

I adopt the following two-stage least squares regressions, where equation 1 is a second

[25] This fecal contamination of groundwater sources is different from the river pollution that is caused by the dumping of fecal sludge emptied from latrines. The former is considered to motivate the IV design, while the latter is the effect I investigate in this paper.

[26] Noncompliance with these requirements in the technical guideline can weaken the first-stage relationship. I discuss the F-statistics of the first-stage relationship below, as well as show the confidence interval of the Anderson and Rubin (1949) test that is robust to the weak instrument in Section 6.1.

stage regression and equation 2 is a first stage regression.

$$Y_{i,d,t} = \alpha + \beta_{IV} Latrine_{d,t} + \gamma_1 Precip_{d,t} + \delta_i + \theta_t + \varepsilon_{i,t} \tag{1}$$

$$Latrine_{d,t} = \pi_1 + \pi_2 AWC_d \cdot Post_t + \pi_3 Precip_{d,t} + \delta_i + \theta_t + \nu_{i,t} \tag{2}$$

where $Y_{i,d,t}$ is a water quality indicator, represented by the logarithm of fecal coliform, at monitoring station i inside district d in year t. $Latrine_{d,t}$ is a number of latrines per square kilometer at the district d of the monitoring station i in year t. $Precip_{d,t}$ is precipitation at the district d in year t, which is added to control for the rainfall and associated floods that may affect both water quality and latrine construction. As an instrument, AWC at district d is interacted with a post-SBM indicator that takes the value one after 2014 when SBM started. δ_i is monitoring station fixed effects, and θ_t is year fixed effects. Standard errors are clustered by district because the variation in the number of latrines is observed at the district level. The coefficient of interest is β_{IV}, and I expect it to be positive.

In the case of health effects, I run a district-level regression, where an outcome variable, $Y_{d,t}$, is diarrheal mortality. In the baseline specification, I focus on post-neonatal mortality because it is the closest available measure to infant mortality, which is often used as an outcome in the context of sanitation and water pollution (Do et al., 2018; Geruso and Spears, 2018).[27] I use district fixed effects instead of monitoring station fixed effects. Standard errors are similarly clustered by district. In this case, the sign of the coefficient of interest, β_{IV}, is determined by the magnitudes of both positive health effects and negative externality.

5.2 Validity of Exclusion Restriction

The IV design builds on a key assumption of exclusion restriction. The instrument, $AWC_d \cdot Post_t$, must affect water quality and health only through the channel of latrine construction after controlling for precipitation, monitoring station (district) fixed effects, and year fixed effects.

When water quality is an outcome, one potential concern is that AWC affects the agricultural yield of crops, which in turn affects the volume of agricultural runoff, leading to a change in the water quality. To address this concern, I choose fecal coliform as a water quality indicator because fecal coliform is unrelated to the production of crops.

There are legitimate concerns that AWC can affect health outcomes through other channels. For instance, AWC might affect the agricultural yield of crops, which in turn determines a household's income, which in turn affects the level of health investments, leading

[27] Post-neonatal mortality and infant mortality refer to the probabilities of a child dying between 28 days after birth and the age of one year and dying between the birth and the age of one year, respectively.

to changes in health conditions.[28] Moreover, AWC might affect the level of groundwater pollution resulting from open defecation, which in turn affects health outcomes.

As a formal test of the validity of the exclusion restriction, I run reduced-form regressions of the outcomes of water quality and health on the interaction of AWC and year dummies. The exclusion restriction suggests that AWC should not affect the outcomes prior to the SBM policy. During the pre-SBM period, AWC is unlikely to affect latrine construction because the official technical guideline that requires the consideration of soil infiltrations had not been published until 2013, just before the start of the SBM. Thus, the association of AWC and outcomes during the pre-SBM period captures the causal pathways other than through latrines. Conversely, AWC is expected to have strong relationships with outcomes after the SBM started to incentivize latrine construction in 2014. Indeed, Figure 7 shows no effects of AWC on both outcomes of water quality and health up to 2013. In contrast, starting from 2014, larger AWC leads to an increase in fecal coliform and a decrease in diarrheal post-neonatal mortality.

As a second test of the validity of the exclusion restriction, I conduct falsification tests that examine the effects on other water quality and health indicators unrelated to fecal contamination. Specifically, I examine the effects of latrine construction on water temperature, pH, and malaria mortality for ages 0-4.[29] The exclusion restriction suggests that latrine construction should not affect these irrelevant outcomes. As expected, I do not find effects on water temperature, pH, and malaria mortality in either IV or DID designs (Columns 1-4 and 11 of Appendix Table B4).[30]

5.3 Upstream-Downstream Specification in Instrumental Variable Design

The negative externalities on water and health may spill over to downstream districts because dumped fecal sludge can flow downstream along rivers. Thus, I additionally examine the effects of upstream latrine construction on downstream water quality and health in the modified IV specification.

This upstream-downstream specification addresses the concern of exclusion restriction in the baseline specification of the IV design. In this specification, I use upstream AWC as an

[28] Although district fixed effects control for the time-invariant agricultural productivity across districts, differential growth in the agricultural yield caused by different levels of AWC might be present, leading to potential differential increases in income and health investment.

[29] This analysis is based on the water quality data of the NWMP and the malaria mortality estimates of IHME (2020a).

[30] As an additional analysis, I adopt the BOD, DO, and Nitrate-Nitrite, which measure water contamination from various pollution sources, as outcomes. I do not find effects on these variables in most cases (Columns 5-10 of Appendix Table B4). These results suggest that there are no other substantial sources of water contamination due to other programs implemented at the same time as the SBM.

instrument for upstream latrine construction and examine the impacts on downstream outcomes. The upstream AWC is not expected to affect downstream health outcomes through a change in income because the upstream AWC is unlikely to be associated with the downstream agricultural output. Thus, using upstream AWC unrelated to downstream health outcomes as an instrument enhances the validity of the exclusion restriction.[31]

I identify upstream-downstream relationships among monitoring stations and districts using the elevation data along 43 major rivers.[32] Thus, this specification focuses on a subset of districts (stations) located along major rivers that have further upstream districts.[33] The upstream districts of a given district (station) are selected as the districts that intersect with river segments whose elevations are higher than the elevation of the given district (station).

The definition of upstream districts, i.e., how far upstream I should search for districts, matters because the pollution decays as it flows downstream. Because the decay rates depend on the temperature and other environmental factors of rivers, I adopt a variety of distances from a given district (station) for identifying upstream districts. Specifically, for a given district (station), the upstream districts are selected from districts that fall within a range of $[X, Y]$ kilometers from the given district (station), where $X \in \{0, 50, 100\}$, $Y \in \{100, 150\}$, and $X < Y$. I use a range of $[0, 150]$ kilometers as the baseline specification, and I conduct robust checks which use either alternative buffer sizes or all upstream districts without buffers.[34]

In this analysis, I use the following regressions 3 and 4 modified from the baseline specification. The independent variable is changed to the upstream number of latrines per square kilometer, and the instrument is changed to the upstream AWC.[35] I also control for AWC in the reference district because the instrument (upstream AWC) can be spatially correlated with AWC in the reference district, which can also affect outcomes. The coefficient of interest, β^U_{IV}, captures the effect of upstream latrine construction, which is the composite of two

[31] To test the validity of the exclusion restriction, I run reduced-form regressions of outcomes on upstream AWC as in Section 5.2. Appendix Figure A2 encouragingly shows no effects of upstream AWC on both water quality and health outcomes during the pre-SBM period.

[32] I focus on major rivers included in the Version 4.1.0 GIS polygons of rivers provided by the Natural Earth. Upstream-downstream relationships along major rivers are less susceptible to measurement errors because the river systems are simpler than those that include hundreds of rivers. I use 90-meter raster digital elevation data, called the Shuttle Radar Topography Mission (SRTM) data Version 4.1 (Reuter et al., 2007).

[33] The focus on major rivers results in a sample of 365 stations in 154 districts in the water quality analysis. In the district-level health analysis, I further drop districts where more than one major rivers flow due to the complexity of determining the upstream-downstream relationships, resulting in a sample of 103 districts.

[34] The same procedure is repeated to identify downstream districts for a placebo test. These are selected as the districts that intersect with river segments whose elevations are lower than the elevation of the given district (station).

[35] If there are multiple upstream districts, I compute the aggregated values of latrines and AWC for upstream districts by taking the average of their values.

underlying effects: (i) the direct effect of upstream latrine construction on outcomes and (ii) the indirect effect of upstream latrine construction on outcomes via latrine construction in the reference district. To examine the latter channel, I also test the effect of upstream latrine construction on the latrine construction in the reference district.[36]

$$Y_{i,d,t} = \alpha + \beta^U_{IV} Upstream\_Latrine_{d,t} + \gamma_1 Precip_{d,t} + \gamma_2 AWC_d \cdot Post_t + \delta_i + \theta_t + \varepsilon_{i,t} \quad (3)$$

$$\begin{aligned} Upstream\_Latrine_{d,t} = \pi_1 &+ \pi_2 Upstream\_AWC_d \cdot Post_t + \pi_3 Precip_{d,t} \\ &+ \pi_4 AWC_d \cdot Post_t + \delta_i + \theta_t + \nu_{i,t} \end{aligned} \quad (4)$$

5.4 Difference-in-Differences Design

I complement the IV design with the DID design to examine the dynamic evolution of the effects of the SBM on water quality. In the DID design, I exploit the fact that all districts had achieved almost universal latrine coverage by the target date of 2019, regardless of their baseline latrine coverage. Thus, districts with lower baseline latrine coverage have experienced a larger increase in latrine coverage. This fact allows me to adopt a DID design that uses baseline latrine coverage as a continuous treatment.[37] As shown in Figure 6, there are substantial differences in the baseline latrine coverage across districts in 2013, which suggests a differential increase in the number of latrines by 2019. This first-stage relationship is empirically shown in the Appendix Figure A3. Then, I expect that districts with higher latrine non-coverage in 2013 have experienced a higher increase in water pollution due to a larger increase in latrine coverage.

In this DID design, I adopt the following baseline regression.[38]

$$Y_{i,d,t} = \alpha + \beta_{DID}(1 - Latrine^{pre}_d) \cdot Post_t + \gamma \mathbf{X_{d,t}} + \delta_i + \theta_{b,t} + \varepsilon_{i,t} \quad (5)$$

where $Y_{i,d,t}$ is a water quality indicator, represented by the logarithm of fecal coliform, at monitoring station i inside district d in year t. $Latrine^{pre}_d$ is a latrine coverage in district d in 2013, which was one year before the SBM started. $Post_t$ is an indicator that takes the value one after 2014 when SBM started. $\mathbf{X_{d,t}}$ are a set of control variables, which

[36] Another approach would be to regress outcomes on upstream latrine construction and the latrine construction in a reference district and instrument them with AWC in each area. I do not adopt this approach due to the issue of a weak instrument in the first stage.

[37] This DID design that uses variation in baseline degree of policy implementation is in the same vein as Duflo (2001) and Bleakley (2007).

[38] Recent literature shows that the DID design with a continuous treatment is subject to biased estimates unless alternative (typically stronger) assumptions, other than the parallel trends assumption, are satisfied (Callaway et al., 2021). Therefore, I conduct a robustness check by adopting an alternative design with a binary treatment that compares districts whose baseline latrine coverage is lower than the national median with districts whose baseline coverage is higher than the national median.

are time-varying precipitation and time-invariant district characteristics, including VIIRS nighttime luminosity in 2013, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates in 2011. Time-invariant variables are interacted with year dummies in the regressions. Lastly, monitoring station fixed effects, δ_i, and basin-year fixed effects, $\theta_{b,t}$, are included. Standard errors are clustered by districts since the baseline latrine coverage varies across districts. The coefficient of interest is β_{DID}, and I expect it to be positive.

To examine pre-trends and the dynamic evolution of the treatment effects, I also adopt the following event-study specification.

$$Y_{i,d,t} = \alpha + \sum_{l=2007}^{2019} \beta_l (1 - Latrine_d^{pre}) \cdot T_l + \gamma \mathbf{X_{i,t}} + \delta_i + \theta_{b,t} + \varepsilon_{i,t} \tag{6}$$

where the baseline year is 2013, and T_l is a year dummy variable. The coefficients of interest are the β_l's, that measure the treatment effects on water quality in each year relative to 2013. The β_l's of 2007-2012 are examined to test the assumption of parallel pre-trends, while the β_l's of 2014-2019 capture the dynamic evolution of the treatment effects. Based on the test of parallel pre-trends, I use this DID design only for the water quality outcome.

6 Results

6.1 Effects on Water Quality

I find that latrine construction under the SBM degrades river water quality in both IV and DID designs. In the IV design, Table 2 shows that one additional latrine per square kilometer increases fecal coliform by 3% on average (Column 3). This estimate of the effect on water quality in the IV design is substantially larger than in the OLS regression, which is about 0.6% (Column 1). This difference suggests the downward bias from the endogeneity in the OLS regression, possibly due to reverse causality if increased water pollution impedes latrine construction to avoid further pollution.

The result of the first stage shows the positive association between AWC and the number of latrines as expected (Column 2 of Table 2). Although the F-statistics of the first stage are not low (29.954), I also compute the 95% confidence interval of the Anderson and Rubin (1949) test that is robust to the weak instrument. Reassuringly, the positive left and right ends of the 95% confidence interval ([0.15, 0.49]) show that the result is robust to this Anderson and Rubin (1949) specification.[39]

[39] The Anderson and Rubin (1949) confidence intervals are shown for all following IV results.

A total effect of the SBM (hereinafter called "average policy effect") is a 72% increase in fecal coliform, which shows a substantial negative externality on the water quality (Column 3 of Table 2). The average policy effect is calculated by multiplying the estimated coefficient by the difference between the mean number of latrines per square kilometer during the pre-SBM (2012-2013) period and during the post-SBM period (2014-2019).[40]

I find a similar result in the DID specification. The positive coefficient in Column 4 of Table 2 suggests that latrine construction increases water pollution, although the effect becomes imprecise. In this DID design, the water pollution effects become larger and more precise when I focus on areas with lower STP treatment capacities in the heterogeneity analysis in Section 7.1. On the other hand, I find a null effect in areas with higher treatment capacities, which renders the overall effect in Table 2 imprecise.

These results are consistent with my theoretical prediction that the SBM increases water pollution due to the dumping of fecal sludge from increased latrines.

6.2 Effects on Health

I find that latrine construction under the SBM improves health overall in the IV design. Table 3 reports that one additional latrine per square kilometer reduces the diarrheal post-neonatal mortality per 1,000 people by about 0.029 on average in the IV design, which is a 1.3% reduction from the pre-SBM period. The average policy effect of the SBM is calculated to be a 0.827 reduction in diarrheal post-neonatal mortality per 1,000 people, which amounts to a 36% reduction from the pre-SBM period (Column 3). This positive health effect result is robust to the adoption of diarrheal mortality in other age groups (Appendix Table B3).[41]

These results capture the overall health effect, which is the difference between the direct positive health effect and the negative externality on health due to water pollution. Thus, the overall positive health effect in my analysis suggests that the direct positive health effect outweighs the negative externality on health, as shown in the conceptual framework.

6.3 Effects of Upstream Latrine Construction on Downstream Outcomes

I find that upstream latrine construction degrades downstream water quality while improving downstream health overall in Table 4 in the IV design.[42] First, I find that upstream

[40] This average policy effect is an upper-bound estimate because some constructed latrines may not be attributed to the SBM subsidy. Moreover, when I calculate average policy effects for other results, I use the difference in the mean number of latrines per square kilometer in each sample.

[41] The magnitude of the health effect differs across age groups because of the difference in the mean value of each type of diarrheal mortality.

[42] Table 4 reports results when upstream and downstream districts are defined as those within the range of $[0, 150]$ kilometers from a reference station (district). The results are robust to alternative buffer sizes as

latrine construction increases fecal contamination of rivers in the reference district only when upstream areas have lower treatment capacities (examined more in detail in Section 7.1), although the effect becomes imprecise when I use all observations (Columns 1 and 3-6 of Panel A). This heterogeneity in the effects shows water pollution externalities of latrine construction that extend to downstream districts. On the other hand, I find a null effect of downstream latrine construction on water quality in the reference district, as there should be no water pollution externalities from downstream to upstream districts (Column 2 of Panel A).

Second, I find that upstream latrine construction has reduced diarrheal mortality in the reference district overall (Column 1 of Panel B). Although upstream latrine construction causes water pollution externalities to the reference district, it improves health outcomes in the reference district overall due to separate benefits arising from increased latrine construction in that district (Column 1 of Panel C). The positive net health effect that comes from increased latrine construction outweighs the water pollution externalities. The positive spillover effect of latrine construction from upstream to reference districts can be explained by the fact that these districts are usually located in the same state, given that the buffer sizes for identifying upstream districts are less than or equal to 150 kilometers. Because states play a central role in implementing sanitation policies in India, districts within the same state are likely to undertake a similar level of latrine construction.[43] On the other hand, I find a null effect of downstream latrine construction on health in the reference district (Column 2 of Panel B).

6.4 Robustness Checks

The results are robust to the consideration of spillovers from neighboring districts, influence from urban areas, and a balanced panel.[44]

Spillovers from Neighboring Districts.—The analysis of the baseline specification assumes that water quality in a given monitoring station is affected only by the latrine construction in the district where that monitoring station is located. However, monitoring stations can be situated on rivers that flow along the border of several districts. In this case, water quality

shown in Appendix Table B2.

[43] To directly test this claim, I estimate the intra-cluster correlation coefficient, which measures the proportion of the overall variance that is explained by within-state variance in the number of latrines per square kilometer between 2013 and 2019. The coefficient is estimated to be 0.704. This high coefficient suggests that districts within the same state behave similarly in terms of latrine construction.

[44] I mainly test the robustness of the baseline specification that serves as the basis for the heterogeneity analysis in Section 7, although I include results of heterogeneous effects for the robustness checks on the spillovers from neighboring districts and a balanced panel.

in those stations is likely to be affected by several neighboring districts.

I conduct an additional analysis that incorporates spillover effects from neighboring districts. For the monitoring stations that are located within 2 kilometers of more than one district, I compute the weighted average of variables of neighboring districts by using district areas as weights. The data of other monitoring stations remain unchanged. Then, I run the regressions 1, 2 of the IV design and the regression 5 of the DID design.

As shown in Column 1 of Appendix Table B5, I find results that are similar to the baseline specification. I find a negative effect on water quality, and the estimated coefficients are very similar to those in the baseline specification.

Influence from Urban Areas.—While my focus is on the effects of latrine construction in rural India, it is possible that the baseline specification results are partly driven by latrine construction in urban areas. Therefore, I conduct a robustness check that estimates the effects of the SBM after excluding monitoring stations and districts that are close to urban areas from the sample. Specifically, I drop monitoring stations and districts that are within 50/100/150 kilometers of cities with a population of 1 million and above according to the 2011 Census.

As shown in Appendix Table B6, the results are robust to excluding urban areas regardless of distance in the IV design. As in the baseline specification, I find a negative effect on water quality and an overall positive health effect.

Balanced Panel.—The baseline specification uses unbalanced panel data on water quality, so I conduct a robustness check using a balanced panel. Using the balanced panel mitigates the concern that monitoring stations may have been endogenously installed in less polluted locations over the sample periods. As shown in Column 1 of Appendix Table B7, I similarly find a negative effect on water quality in both IV and DID designs.

7 Heterogenous Effects of Sanitation

To explore the mechanism behind the negative externalities, I test the heterogeneous effects of latrine construction. Specifically, to test the mechanism of the dumping of fecal sludge (poor treatment of fecal sludge), I examine whether the negative externalities are larger in areas with lower treatment capacities of fecal sludge and in areas with higher exposure to river pollution.

7.1 Heterogenous Effects by Treatment Capacity of Fecal Sludge

Motivated by the theoretical hypotheses regarding the differential effects of the SBM, I examine how negative externalities on water quality and health vary by the level of complementary investment in the treatment of fecal sludge. Specifically, I use geographical variation in the treatment capacities of STPs. Based on the inventory of STPs compiled by the CPCB (CPCB, 2015), I calculate the STP capacities at both state and district levels in 2013, one year before the SBM started.[45] In the baseline specification, I compare effects in states/districts that have higher treatment capacities than the median in the sample with those in states/districts with lower treatment capacities.[46] In the upstream-downstream specification, I similarly examine the heterogeneous effects by the different levels of treatment capacities in upstream states/districts.

Effects on Water Quality.—I find that the negative externality on water quality is substantial in areas with lower treatment capacities in the IV design. As shown in Panel A of Table 5, one additional latrine per square kilometer increases fecal coliform by 3.7% in states with lower treatment capacities (Column 3). On the other hand, I find no effect in states with higher treatment capacities (Column 2). Similarly, I find that one additional latrine per square kilometer increases fecal coliform by 5.1% in districts with lower treatment capacities (Column 5), although the effect becomes insignificant in districts with higher treatment capacities (Column 4). In the upstream-downstream specification, I similarly find a negative externality of upstream latrine construction on downstream water quality when upstream states/districts have lower treatment capacities (Columns 4 and 6 of Panel A of Table 4).

I find similar results in the DID design in Panel B of Table 5. The coefficients of $(1 - Latrine_d^{pre}) \cdot Post_t$ show that a district with baseline latrine coverage of 50% would experience an increase in fecal coliform of about 75-90%, relative to a district with 100% baseline latrine coverage, in areas with lower treatment capacities (Columns 3 and 5). Considering the fact that the baseline latrine coverage was 39.2% in 2013, the average effects of the SBM in states with lower treatment capacities can be calculated as $(1 - 0.392) \times 1.790 = 1.088$ in the DID design, which is relatively close to the average policy effect (0.976) in the IV design. On the other hand, consistent with the results of the IV design, I do not find negative externality in the areas with higher treatment capacities (Columns 2 and 4).

The DID event study design shows the negative externality on water quality in areas

[45] The district-level STP capacities are highly susceptible to measurement errors due to missing observations of STPs in the CPCB inventory. Some districts may be flagged as districts with zero treatment capacity due to missing observations, even if they actually have STPs. Therefore, I also use state-level STP capacities, which are less susceptible to measurement errors due to further aggregation.

[46] The median value is calculated after setting zero capacity for the states/districts with no STP.

with lower treatment capacities has become substantial two years after the start of SBM, and this effect has become larger over time. The estimated coefficients from the event-study specification in equation 6 are reported in Figure 8. First, Figure 8 reassuringly shows no differential pre-trends for all panels, which enhances the validity of the parallel pre-trends assumption. Second, Figure 8 highlights that the negative externality in states with lower treatment capacities has become substantial since 2016, two years after the start of the SBM (Panel B).[47] This lagged effect is consistent with the fact that a differential increase in the number of latrines among districts with different levels of baseline coverage starts around 2016 in Appendix Figure A3.[48] Moreover, this negative externality on water quality become larger over time from 2016 to 2019.

These differential effects of the SBM by the treatment capacity of fecal sludge suggest that the dumping of fecal sludge emptied from latrines is the main mechanism accounting for increased river pollution. These findings are consistent with the theoretical prediction that the magnitude of water pollution is larger in the case of lower treatment capacity due to larger marginal damage. Conversely, the null effect on water quality in areas with higher treatment capacities suggests it is unlikely the effect is caused by other channels (e.g., the seepage of fecal matter from latrines to rivers).

Effects on Health.—The analysis of heterogeneous effects allows me to explicitly investigate the negative externality on health. The negative externality can be captured as a difference between the health effect of areas with lower treatment capacities (significant river pollution) and that of areas with higher treatment capacities (insignificant river pollution).

Panel C of Table 5 shows the results of heterogeneous effects on diarrheal post-neonatal mortality by treatment capacities at both state and district levels in the IV design. I find that the magnitude of the positive health effect is 0.064 (3% decrease) in states with higher treatment capacities (Column 2), while the magnitude reduces to 0.020 (1% decrease) in states with lower treatment capacities (Column 3). The average policy effect of the SBM is a 0.625 decrease (26% decrease) in diarrheal mortality in states with lower treatment capacities, which is about two-thirds smaller than the effect of a 1.507 decrease (71% decrease) in states with higher treatment capacities (Columns 2-3). This difference in the magnitude of positive health effects is statistically significant (p-value = 0.003). The difference in the coefficients becomes imprecise when I compare the effects by district-level treatment capacities (Columns

[47] Appendix Figure A4 shows event study plots that compare districts with higher and lower treatment capacities. Because I find differential pre-trends in the case of districts with lower treatment capacities (Panel B), I focus on the results based on state-level variation in treatment capacities.

[48] These results are robust to an alternative specification of a binary treatment indicator that takes the value one when district's baseline latrine coverage is lower than the national median (Appendix Table B1 and Appendix Figure A5).

4-5).

In the upstream-downstream specification of the IV design, I find that the upstream latrine construction has smaller positive health effects of decreasing diarrheal mortality in the reference district when the upstream states/districts have lower treatment capacities (Columns 4 and 6 of Panel B of Table 4). In these cases of lower treatment capacities, the positive health effect of upstream latrine construction becomes null, which suggests that the positive net health effect that comes from increased latrine construction in the reference district is completely offset by the water pollution externalities.

These results, together with those on water quality effects, suggest that the increased water pollution due to the SBM, which is substantial in areas with lower treatment capacities, has negative health consequences. Although the overall health effect is positive, the water pollution externalities reduce the magnitude of this positive health effect, as predicted in the theoretical prediction.

7.2 Heterogenous Effects on Health by Exposure to River Pollution

I examine how health effects vary by the intensity of exposure to river pollution. The negative externality on health is expected to be larger for those with greater exposure to river pollution. Proximity to rivers increases exposure to river pollution because people living close to rivers are more likely to use river water for bathing, consumption, household use, etc. Thus, I examine how health effects vary by the proximity to rivers.

To test these heterogeneous effects on health, I construct an indicator of how many people live near rivers based on the VIIRS nighttime light data in 2013. First, I calculate the total nighttime luminosity of each district. Second, I calculate the total nighttime luminosity of areas within 5/10/15 kilometers of rivers for each district.[49] Third, I calculate the district-level ratio of nighttime luminosity within specified distances from rivers by dividing the value of the second step by the value of the first step.[50]

Based on this constructed indicator, I compare health effects in districts with higher exposure to river pollution with those in districts with lower exposure in the IV design. A given district is defined as highly exposed to river pollution if its ratio of the total nighttime luminosity of the area close to rivers is higher than the sample median.

Table 6 shows that positive health effects are smaller in districts with a higher proportion

[49] I use rivers $\geq$30-meter wide at mean annual discharge, available in the Global River Widths from Landsat (GRWL) Database (Allen and Pavelsky, 2018). This dataset covers more rivers, including smaller ones, than the dataset of major rivers used in the upstream-downstream analysis.

[50] One limitation of using nighttime light data as a proxy of population density near rivers is that this data cannot distinguish urban from rural populations. If the population density near rivers is different for urban and rural areas within a district, this paper does not reflect that difference.

of nighttime luminosity near rivers, i.e., higher exposure to river pollution. The estimated coefficient is about -0.024 in higher exposure districts (Columns 1, 3, and 5), while the coefficient is about -0.040 in lower exposure districts (Columns 2, 4, and 6). These differences confirm the negative externality on health due to increased water pollution under the SBM.

8 Conclusion

My analysis documents an unintended negative consequence of latrine construction in India. Although open defecation has been commonly blamed for causing negative externalities, I show that latrine construction has larger water pollution externalities than open defecation due to poor treatment of fecal sludge. I then show that investments in latrines are less effective at improving child health in areas where the water pollution effects are larger.

Specifically, I examine the consequences of India's nationwide sanitation policy, the SBM. I exploit two features of the SBM to identify its causal effects on water quality and health. First, the fact that soil infiltration rates determine the cost and difficulty of latrine construction according to the official technical guidelines renders soil infiltration rates suitable as an instrument for latrine construction. Second, the fact that all districts had achieved almost universal latrine coverage by the target date, regardless of their baseline latrine coverage, allows me to use the baseline coverage as a continuous treatment.

Based on these two identification strategies, I find that the SBM increases river pollution by 72%, which is a substantial effect. The negative externality on water quality exists only in areas with lower treatment capacities, where the dumping of fecal sludge is more likely to happen. Moreover, I show that the SBM reduces diarrheal mortality by 36% overall. However, this positive health effect is two-thirds smaller in states with lower treatment capacities (26% reduction) than in states with higher treatment capacities (71% reduction).

The back-of-the-envelope calculations show that the health benefits are worth the cost of the SBM policy. The health benefits, i.e., reduction in diarrheal post-neonatal mortality, are calculated to be 16.9 million USD,[51] almost equivalent to the subsidy cost for latrine construction (17.4 million USD) at the district level.[52] The health benefits would be larger than this estimate if I took into account the health effects for other age groups and other

[51] The health benefits are estimated by multiplying the total number of reduced mortalities under the SBM (30.3) by the estimate of the value of a statistical life in India (0.56 million USD according to Majumder and Madheswaran (2018)). The total number of reduced mortalities is calculated based on the estimated average policy effect (0.827 per 1,000 people) and the estimate of the district-level mean population of age 0-1 (0.36 million people). This population estimate is calculated from the district-level mean population (1.57 million people) and the percentage of population age 0-4 (9.32%) in the 2011 Census.

[52] The cost is calculated by multiplying the amount of the SBM subsidy (150 USD) by the mean change in the number of latrines (0.11 million).

benefits such as improved educational outcomes. Although this result suggests that the SBM is successful overall, sufficient treatment of fecal sludge would increase the health effects even more with a low additional cost. The additional benefits of higher treatment capacity are similarly calculated to be 18.1 million USD, which is larger than the additional cost of constructing and operating more sewage treatment plants (11.5 million USD).[53]

My results present several important policy implications for developing countries promoting sanitation and other environmental and health policies. The first clear implication is that policy-makers should consider the possibility of negative externalities on water quality and health. An enabling environment that includes effective treatment of fecal sludge can make sanitation policies more effective. Accordingly, the Indian government has been recently shifting its focus to the construction of fecal sludge treatment plants under the second phase of the SBM from 2020. Future studies may investigate the causal effects of this increase in the treatment of fecal sludge on water quality and health because my approach herein is to examine heterogeneous effects by the baseline variation in the treatment capacity of fecal sludge.

Second, my findings on the negative externalities have implications for other policies, such as waste management. Waste management policy similarly requires consideration of the various stages involved, ranging from the collection of waste to safe recycling and disposal of waste. Focusing only on the collection of waste may cause negative externalities on the environment due to untreated waste. Investigating the existence of negative externalities associated with other similar policies may be a fruitful area for future research.

[53] Additional benefits are calculated based on the difference in the estimated average policy effects between higher and lower treatment capacities at the state level (1.507-0.625=0.882 per 1,000 people). Additional costs are calculated based on the capital and O&M cost for 15 years (0.23 million USD/million liter per day) of the most common technology, Upflow Anaerobic Sludge Blanket (estimated based on CPCB (2013)), and the district-level difference in STP capacity between states with higher and lower treatment capacities.

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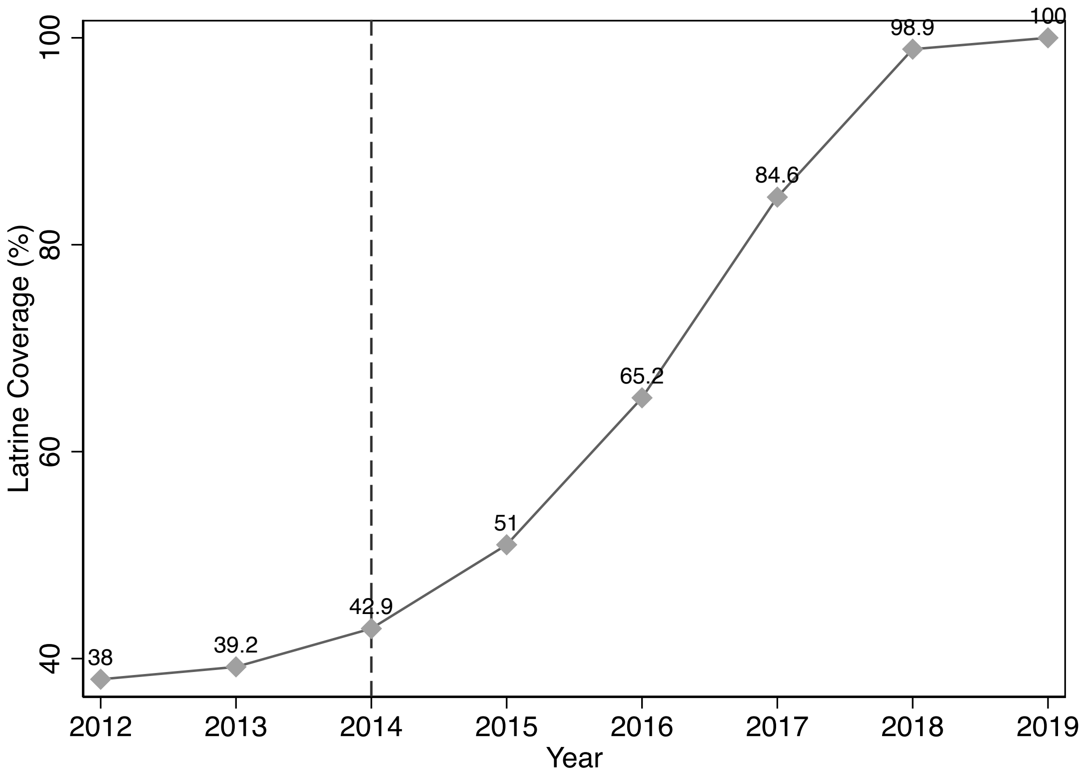
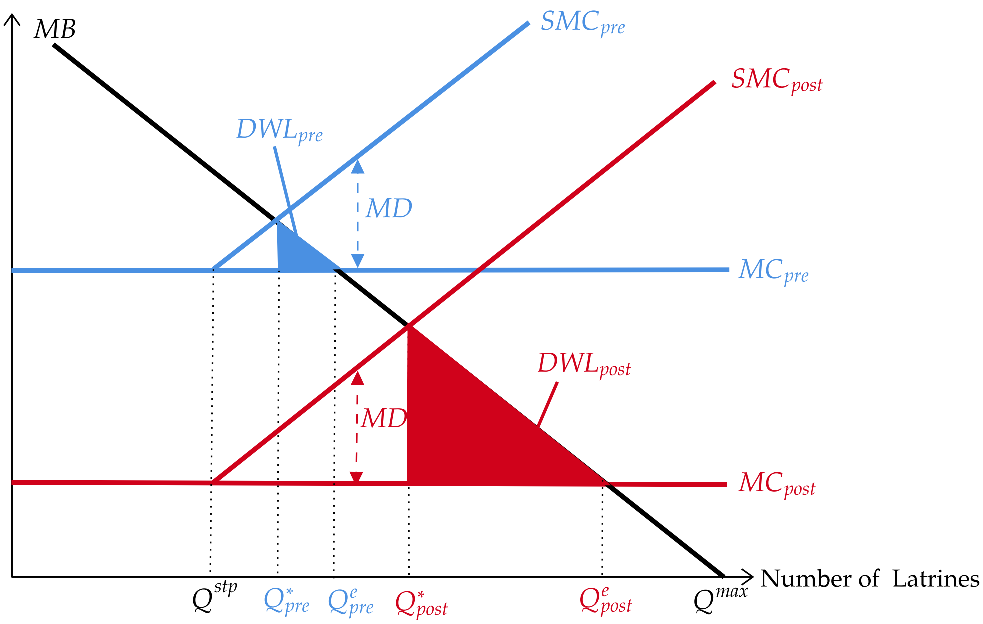


Figure 1: Latrine Coverage in Rural India

Notes: This figure documents the proportion of households that have latrines in rural India between 2012 and 2019. A vertical dashed line shows the starting year of the Swachh Bharat Mission.

Panel A. Treatment Capacity Low



Panel B. Treatment Capacity High

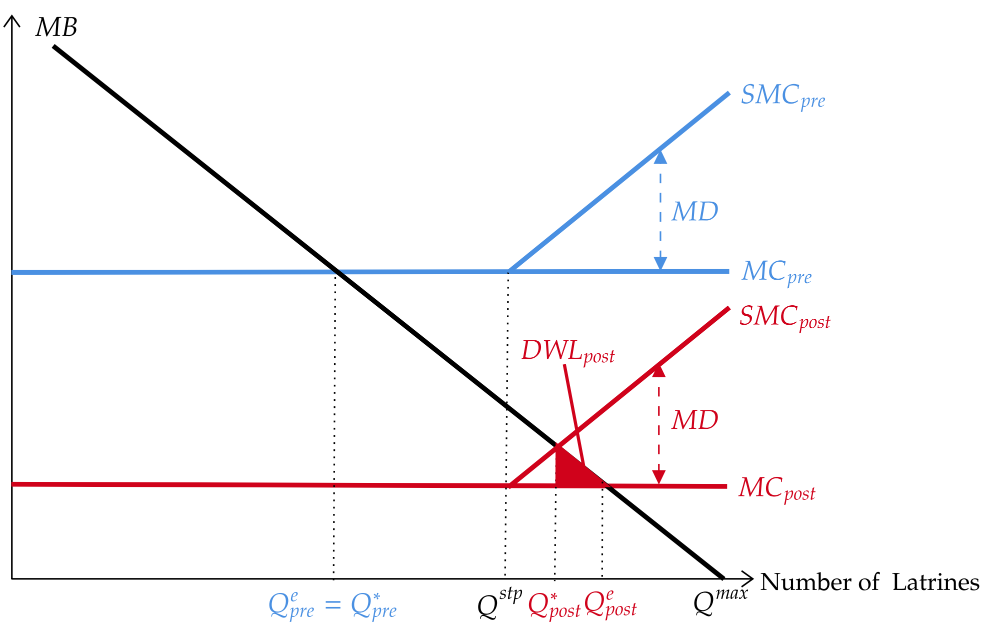
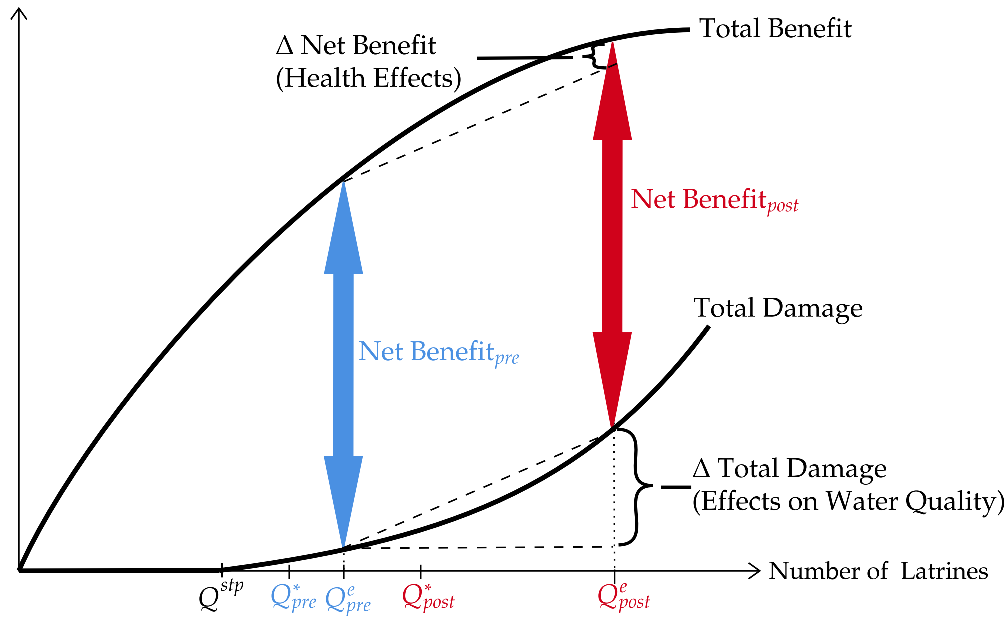


Figure 2: Welfare Effects of the Swachh Bharat Mission

Notes: This figure examines how the subsidy under the SBM changes the deadweight loss (DWL) in two cases: (A) low treatment capacity (low Q^{stp}) and (B) high treatment capacity (high Q^{stp}). The subsidy shifts down the marginal cost (MC) from MC^{pre} to MC^{post}. Marginal damage (MD) represents the negative externality on health, which occurs when the number of latrines is larger than the treatment capacity level (Q^{stp}). Marginal benefit (MB) represents direct health benefits because of reduced open defecation. This figure shows that DWL increases more significantly in the case of low treatment capacity in Panel A.

Panel A. Treatment Capacity Low



Panel B. Treatment Capacity High

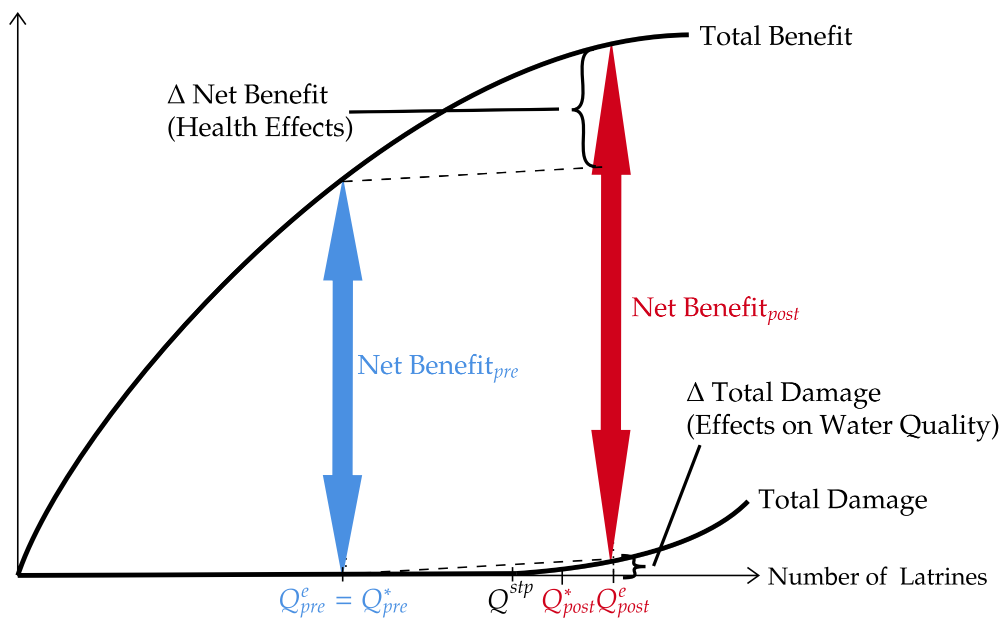


Figure 3: Effects of the Swachh Bharat Mission on Water Quality and Health

Notes: This figure examines how the SBM affects water quality and health in two cases: (A) low treatment capacity (low Q^{stp}) and (B) high treatment capacity (high Q^{stp}). Total benefit and total damage in this figure are based on the marginal benefit and marginal damage plotted in Figure 2. Effects on health and water quality are represented by the changes in net benefit and total damage, respectively. This figure shows that SBM improves health overall and increases water pollution. In the case of low treatment capacity in Panel A, the magnitude of health effects is smaller, and the magnitude of effects on water quality is larger.

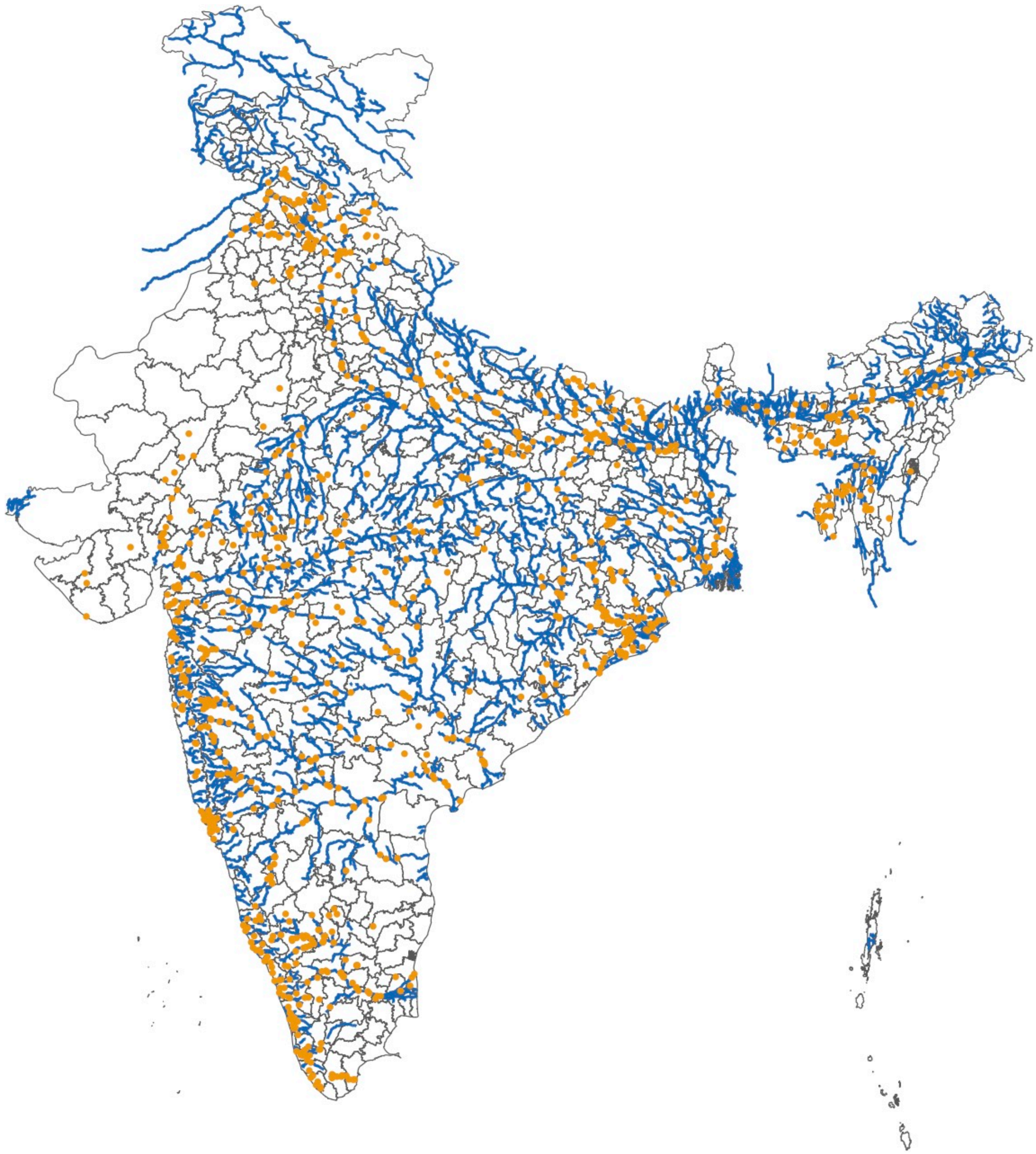


Figure 4: Distribution of Water Quality Monitoring Stations in India

Notes: This figure shows water quality monitoring stations in orange dots, district boundaries in black lines, and rivers in blue lines. The data source of river lines is Allen and Pavelsky (2018).

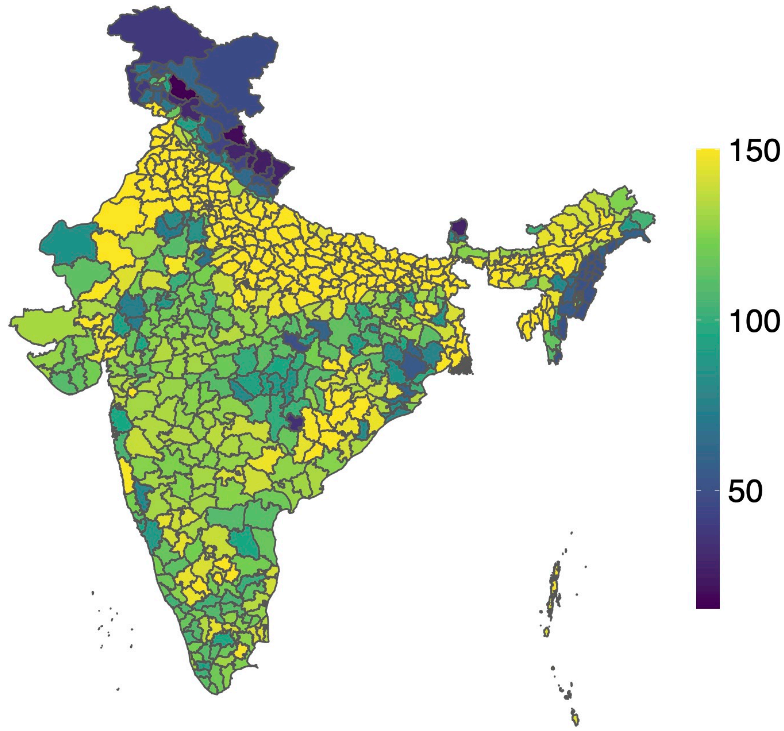


Figure 5: Available Water Capacity (mm/m) across Districts

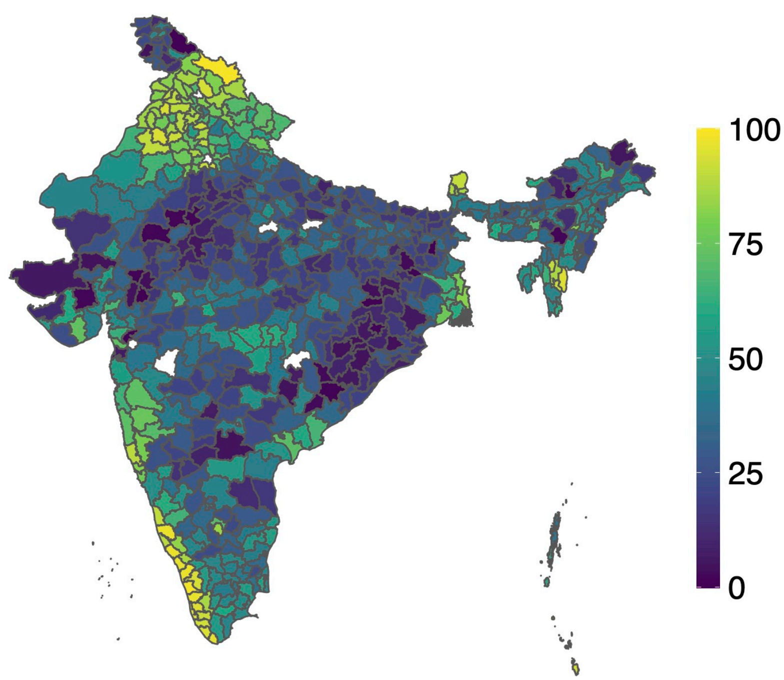


Figure 6: Latrine Coverage (%) in 2013 across Districts

Notes: Districts with no data on latrine coverage are displayed to be blank. These districts correspond to urban areas where latrine data are not recorded under the SBM.

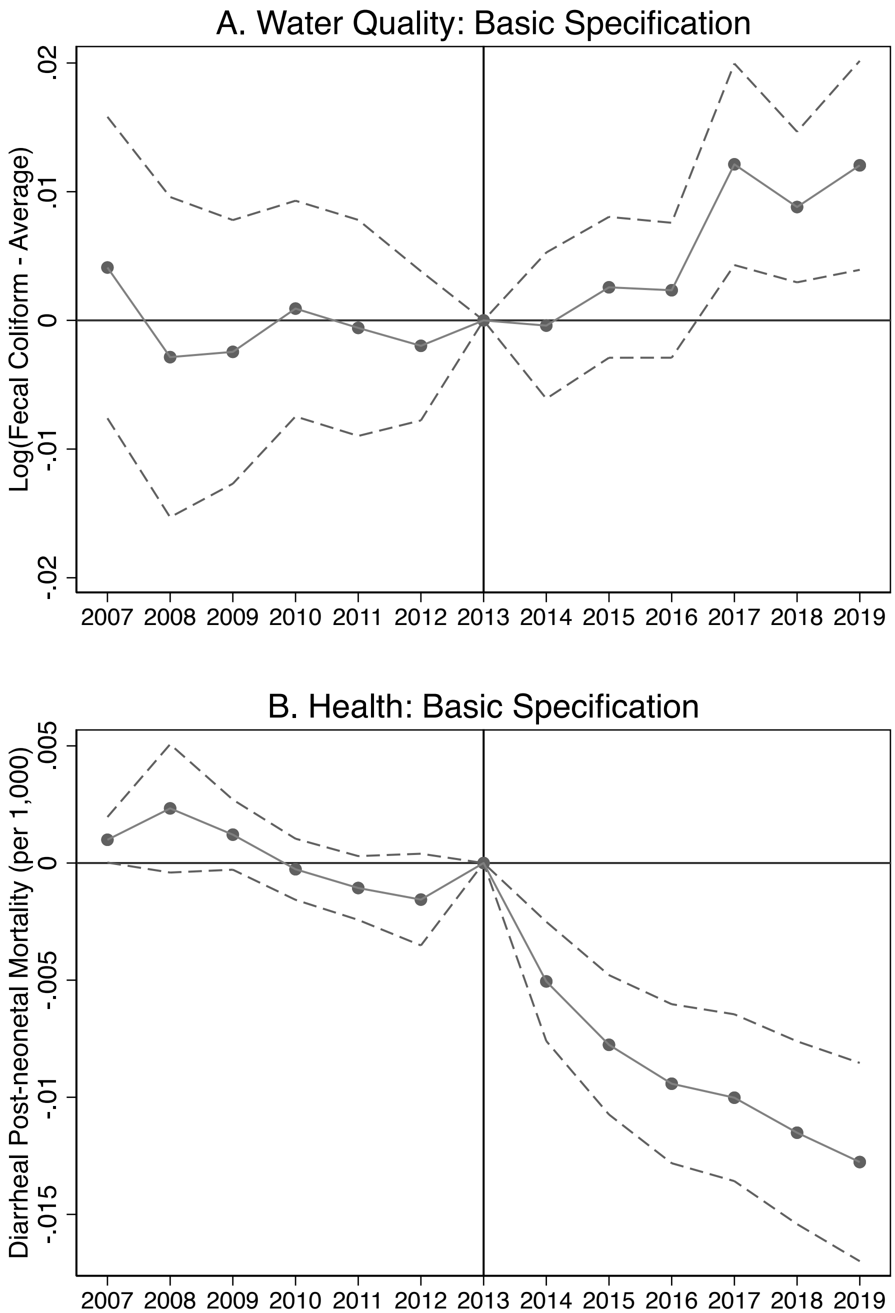


Figure 7: Event Study Plots of Reduced-Form Regressions of AWC

Notes: This figure shows the regression coefficients of the logarithm of fecal coliform (Panel A) and diarrheal post-neonatal mortality per 1,000 people (Panel B) on the interaction terms between AWC and year dummies. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the district level. Panel A includes monitoring station fixed effects, year fixed effects, and precipitation as a control, while Panel B includes district fixed effects, year fixed effects, and precipitation as a control.

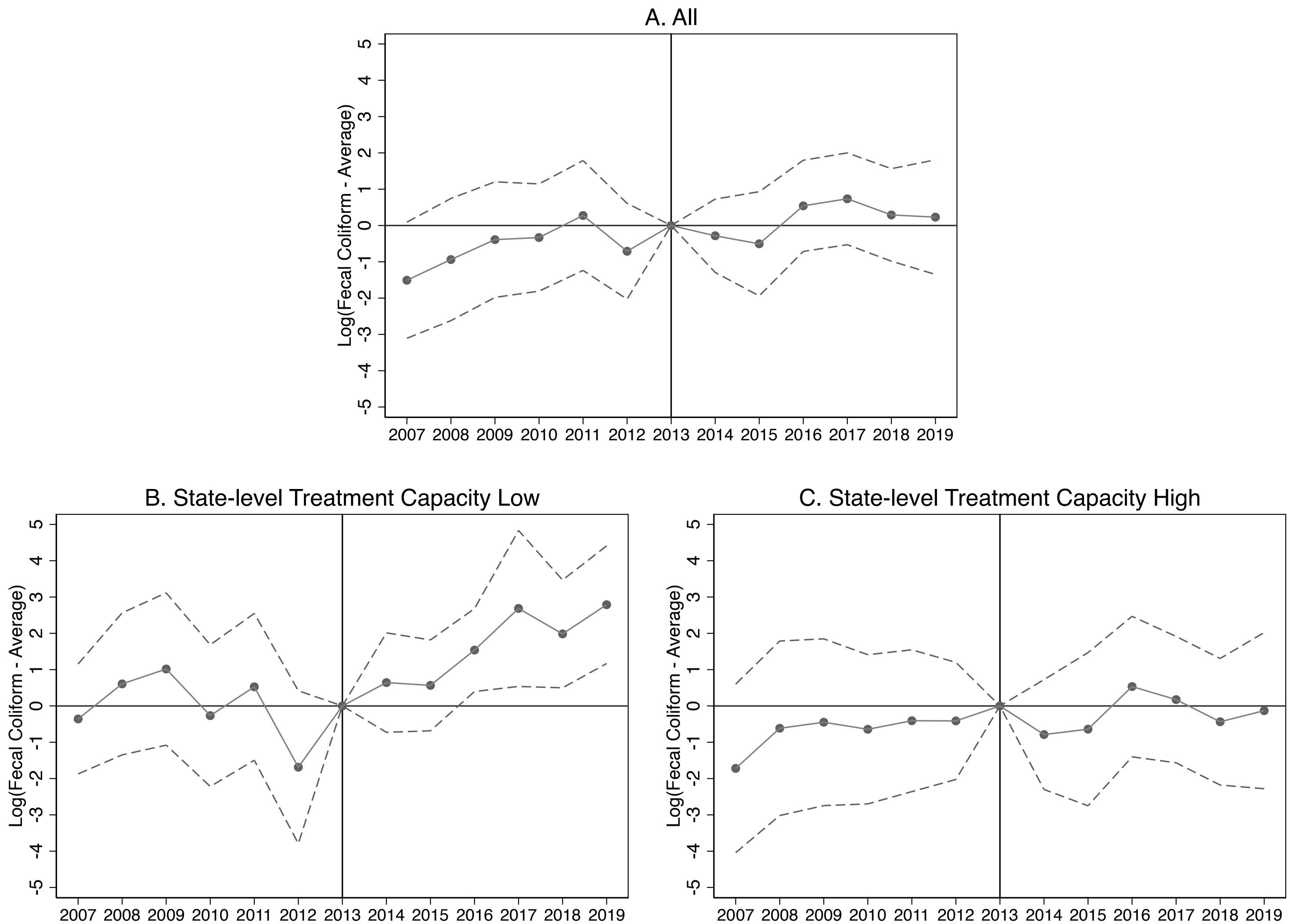


Figure 8: The Dynamic Effects on Water Pollution (Log of Fecal Coliform)

Notes: This figure shows the regression coefficients of the logarithm of fecal coliform in equation 6. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the district level. All regressions include monitoring station fixed effects, basin-year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates.

Table 1: Summary Statistics

	Mean	SD	Min	Max	Observations
Panel A. Time-varying variables: 2007-2013					
Fecal coliform - average (thousand MPN/100ml)	2606.42	143774.77	0	10000035	4939
Diarrheal early-neonatal mortality (per 1000 people)	20.2	13.65	0.5	71.86	2359
Diarrheal late-neonatal mortality (per 1000 people)	9.22	6.19	0.23	32.41	2359
Diarrheal post-neonatal mortality (per 1000 people)	2.69	1.8	0.07	9.48	2359
Diarrheal age 1-4 mortality (per 1000 people)	0.48	0.34	0.01	1.83	2359
Diarrheal under 5 mortality (per 1000 people)	1.07	0.72	0.03	3.87	2359
Malaria age 0-4 mortality (%)	0.02	0.04	0	0.38	2359
Number of latrines (ten thousand)	12.93	13.39	0.01	89.7	586
Number of latrines per sq. km	35.55	41.92	0.03	283.01	586
Latrine coverage (%)	43	25.48	0.08	100	586
Precipitation (mm)	1341.98	778.05	214.05	5589.17	1946
Panel B. Time-varying variables: 2014-2019					
Fecal coliform - average (thousand MPN/100ml)	722.17	30385.66	0	1750013	5553
Diarrheal early-neonatal mortality (per 1000 people)	9.79	7.28	0.29	35.57	2022
Diarrheal late-neonatal mortality (per 1000 people)	4.64	3.44	0.14	16.76	2022
Diarrheal post-neonatal mortality (per 1000 people)	1.46	1.07	0.05	5.21	2022
Diarrheal age 1-4 mortality (per 1000 people)	0.2	0.15	0.01	0.73	2022
Diarrheal under 5 mortality (per 1000 people)	0.51	0.38	0.02	1.86	2022
Malaria age 0-4 mortality (%)	0.01	0.04	0	0.33	2022
Number of latrines (ten thousand)	22.52	18.96	0.01	146.87	1814
Number of latrines per sq. km	59.06	57.05	1.12	430.09	1814
Latrine coverage (%)	76.78	27.43	3.58	100	1814
Precipitation (mm)	1312.23	878.46	196.09	10061.3	1814
Panel C. Variables not varying over time					
Available water storage capacity (mm/m)	128.03	25.91	19.79	150	337
District-level capacity of sewage treatment plants (MLD) - 2013	28.17	105.03	0	947.5	337
State-level capacity of sewage treatment plants (MLD) - 2013	709.5	782.06	0	2307.75	337
Population (thousand) - 2011	1572.08	1077	28.99	6074.19	337
% Scheduled caste population - 2011	16.75	9.69	0	53.39	337
% Scheduled tribe population - 2011	16.98	25.24	0	98.10	337
% Literate population - 2011	61.16	10.44	28.66	88.7	337
VIIRS nighttime luminosity (nW/cm2/sr) - 2013	0.71	1.57	0.01	17.98	337
Ratio of total nighttime luminosity within 5 km of rivers - 2013	0.38	0.23	0	1	317

Notes: This table shows summary statistics of time-varying variables for pre-SBM periods (2007-2013) in Panel A and post-SBM periods (2014-2019) in Panel B, and summary statistics of time-invariant variables in Panel C. The latrine data are available only from 2012-2019, while data of other time-varying variables are available from 2007-2019. MPN and MLD denote "most probable number" and "million liters per day," respectively.

Table 2: The Effect on Water Quality (Log of Fecal Coliform (FCf))

	OLS	IV - First Stage	IV - Second Stage	DID
	(1) Log(FCf)	(2) # of Latrines per sq. km	(3) Log(FCf)	(4) Log(FCf)
Number of latrines per sq. km	0.006***		0.030***	
	(0.002)		(0.008)	
AWC * Post (=1)		0.283***		
		(0.052)		
(1 - 2013 Latrine Coverage) * Post (= 1)				0.647
				(0.527)
Observations	7,201	7,201	7,201	10,385
R^2	0.020	0.091	-	0.860
Number of Stations	1,189	1,189	1,189	1,187
Number of Districts	337	337	337	335
KP F-Stat	-	29.954	-	-
AR 95% CI	-	-	[.015, .049]	-
Average Policy Effect	0.142	-	0.719	-

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Regressions of Columns 1-3 include monitoring station fixed effects, year fixed effects, and precipitation as a control. A regression of Column 4 includes monitoring station fixed effects, basin-year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer after the SBM started in 2014.

Table 3: The Effect on Health (Diarrheal Post-neonatal Mortality (per 1,000 people))

	OLS	IV - First Stage	IV - Second Stage
	(1)	(2)	(3)
	Diarrheal Mortality	# of Latrines per sq. km	Diarrheal Mortality
Number of latrines per sq. km	-0.007***		-0.029***
	(0.001)		(0.005)
AWC * Post (=1)		0.244***	
		(0.039)	
Observations	2,696	2,696	2,696
R^2	0.657	0.131	-
Number of Districts	337	337	337
KP F-Stat	-	39.248	-
AR 95% CI	.	-	[-.042, -.021]
Mean of Dep. Variable	2.282	33.374	2.282
Average Policy Effect	-0.188	-	-0.827

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All regressions include district fixed effects, year fixed effects, and precipitation as a control. The sample is limited to districts that have monitoring stations used in the specification of water quality. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer after the SBM started in 2014.

Table 4: Upstream-Downstream Analysis

	All		State-level Capacity		District-level Capacity	
	(1) All	(2) All	(3) High	(4) Low	(5) High	(6) Low
Panel A. Dependent Variable: Log(Fecal Coliform)						
Upstream number of latrines per sq. km	0.015		-0.046	0.031***	-0.004	0.037*
	(0.011)		(0.031)	(0.011)	(0.011)	(0.023)
Downstream number of latrines per sq. km		0.050				
		(0.042)				
Observations	2,228	2,215	1,109	1,117	1,097	1,131
Number of Stations	365	365	171	194	180	185
Number of Districts	154	147	73	84	75	93
KP F-Stat	50.475	2.391	19.519	41.162	53.262	15.137
AR 95% CI	[-.008, .039]	[..., ...]	[-.111, .037]	[.010, .063]	[-.033, .018]	[-.014, .121]
Panel B. Dependent Variable: Diarrheal Post-neonatal Mortality (per 1,000 people)						
Upstream number of latrines per sq. km	-0.011*		-0.041***	-0.010	-0.014**	-0.000
	(0.006)		(0.010)	(0.006)	(0.007)	(0.010)
Downstream number of latrines per sq. km		-0.025				
		(0.016)				
Equality Test (Upstream)			$p = 0.015$		$p = 0.280$	
Observations	824	760	432	392	456	368
Number of Districts	103	95	54	49	57	46
KP F-Stat	78.696	2.375	33.304	33.484	59.873	18.756
AR 95% CI	[-.023, .001]	[..., .023]	[-.073, -.024]	[-.026, .002]	[-.030, -.000]	[-.029, .026]
Mean of Dep. Variable	2.576	2.621	2.534	2.623	2.428	2.759
Panel C. Dependent Variable: Number of Latrines per sq. km in Reference District (district-level analysis)						
Upstream number of latrines per sq. km	0.726***		1.327***	0.684***	0.649***	0.907**
	(0.154)		(0.214)	(0.160)	(0.170)	(0.358)
Downstream number of latrines per sq. km		1.637**				
		(0.740)				

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample is limited to monitoring stations (Panel A) and districts (Panels B and C) located along major rivers in India. Observations, number of districts, and KP F-Stat of Panel C are the same as Panel B. Upstream and downstream districts are defined as those within the range of $[0, 150]$ kilometers from a reference station/district. Panel A includes monitoring station fixed effects, year fixed effects, and the following controls: precipitation and the interaction of AWC and post-SBM indicator of a reference district. Panels B and C include district fixed effects, year fixed effects, and the same controls as Panel A. Column 3 reports a result in upstream states where treatment capacities of sewage treatment plants are higher than the median, while Column 4 reports a result in upstream states with lower treatment capacities. Similarly, Columns 5 and 6 compare results based on the different levels of upstream treatment capacities at the district level. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. The open-ended confidence intervals show that the searched grids do not extend far enough to capture the point where the rejection probability crosses above the 95%.

Table 5: The Effects on Water Quality and Health by Fecal Sludge Treatment Capacity

	All	State-level Capacity		District-level Capacity	
	(1)	(2)	(3)	(4)	(5)
	All	High	Low	High	Low
Panel A. Dependent Variable: Log(Fecal Coliform) - IV Design					
Number of latrines	0.030***	-0.031	0.037***	0.014	0.051***
per sq. km	(0.008)	(0.025)	(0.007)	(0.009)	(0.017)
Observations	7,201	3,453	3,748	2,902	4,299
Number of Stations	1,189	579	610	466	723
Number of Districts	337	182	155	96	241
KP F-Stat	29.954	7.576	39.516	13.648	11.931
AR 95% CI	[.015, .049]	[-.123, .018]	[.025, .054]	[-.012, .034]	[.023, .105]
Average Policy Effect	0.719	-0.666	0.976	0.286	1.342
Panel B. Dependent Variable: Log(Fecal Coliform) - DID Design					
(1 - 2013 Latrine	0.647	0.372	1.790***	0.496	1.496**
Coverage) * Post (= 1)	(0.527)	(0.775)	(0.660)	(0.911)	(0.654)
Observations	10,385	5,075	5,281	4,240	6,110
R^2	0.860	0.869	0.883	0.881	0.879
Number of Stations	1,187	577	606	465	719
Number of Districts	335	182	151	95	238
Panel C. Dependent Variable: Diarrheal Post-neonatal Mortality (per 1,000 people)					
Number of latrines	-0.029***	-0.064***	-0.020***	-0.023***	-0.032***
per sq. km	(0.005)	(0.013)	(0.004)	(0.006)	(0.008)
Equality Test		$p = 0.003$		$p = 0.384$	
Observations	2,696	1,096	1,600	768	1,928
Number of Districts	337	137	200	96	241
KP F-Stat	39.248	16.295	37.216	22.345	18.092
AR 95% CI	[-.042, -.021]	[-.110, -.045]	[-.030, -.013]	[-.044, -.013]	[-.057, -.021]
Mean of Dep. Variable	2.282	2.132	2.386	1.753	2.493
Average Policy Effect	-0.827	-1.507	-0.625	-0.570	-0.960

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Panel A includes monitoring station fixed effects, year fixed effects, and precipitation as a control. Panel B includes monitoring station fixed effects, basin-year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates. Panel C includes district fixed effects, year fixed effects, and precipitation as a control. Column 2 reports a result in states where treatment capacities of sewage treatment plants are higher than the median, while Column 3 reports a result in states with lower treatment capacities. Similarly, Columns 4 and 5 compare results based on the different levels of treatment capacities at the district level. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. The open-ended confidence interval shows that the searched grids do not extend far enough to capture the point where the rejection probability crosses above the 95%. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer after the SBM started in 2014.

Table 6: The Effects on Health by Exposure to River Pollution (Diarrheal Post-neonatal Mortality (per 1,000 people))

	Closeness to Rivers - 5km		Closeness to Rivers - 10km		Closeness to Rivers - 15km	
	(1) High	(2) Low	(3) High	(4) Low	(5) High	(6) Low
Number of latrines per sq. km	-0.024***	-0.043**	-0.025***	-0.040**	-0.024***	-0.044**
	(0.004)	(0.021)	(0.004)	(0.016)	(0.004)	(0.019)
Observations	1,264	1,272	1,280	1,288	1,296	1,296
Number of Districts	158	159	160	161	162	162
KP F-Stat	50.344	4.199	36.650	6.929	38.835	5.270
AR 95% CI	[-.033, -.017]	[..., -.019]	[-.036, -.017]	[..., -.019]	[-.034, -.017]	[..., -.022]
Mean of Dep. Variable	2.513	2.163	2.461	2.182	2.499	2.125
Average Policy Effect	-0.792	-1.057	-0.831	-0.966	-0.782	-1.086

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All regressions include district fixed effects, year fixed effects, and precipitation as a control. Column 1 reports a result in districts where the ratios of total nighttime luminosity within 5 kilometers of rivers are higher than the median, while Column 2 reports a result in districts with lower ratios. Columns 3-6 similarly report results when the distance is changed to 10 and 15 kilometers. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. The open-ended confidence interval shows that the searched grids do not extend far enough to capture the point where the rejection probability crosses above the 95%. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer after the SBM started in 2014.

Appendix

Unintended Consequences of Sanitation: Negative Externalities on Water Quality and Health in India

Kazuki Motohashi

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A Additional Figures

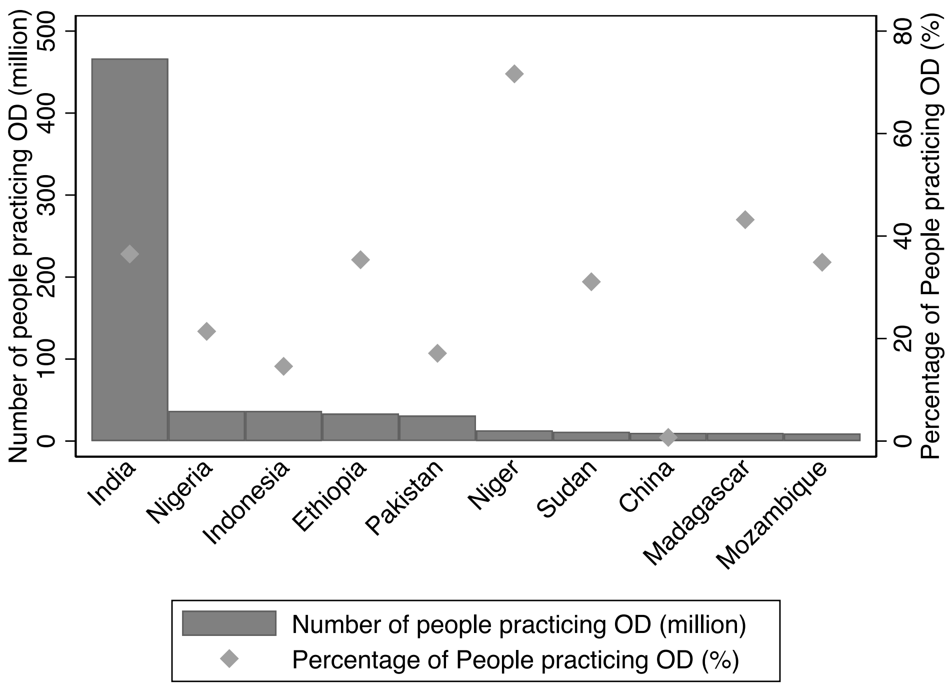
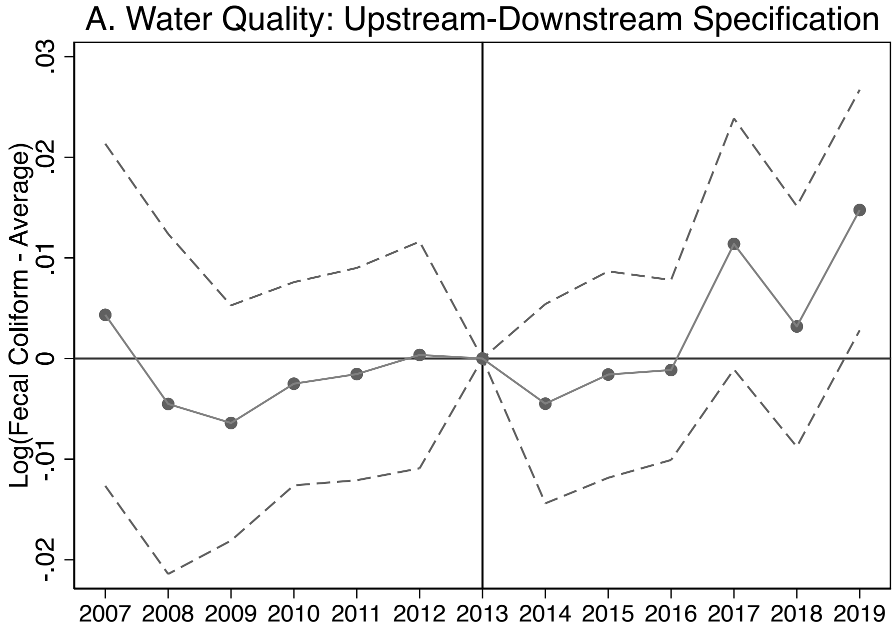


Figure A1: Top 10 Countries by the Number of People Practicing Open Defecation in 2013

Notes: This figure documents the top 10 countries by the number of people practicing open defecation. It plots both the number of people practicing open defecation and the percentage of people practicing open defecation for these 10 countries. The data source is the database of the WHO/UNICEF Joint Monitoring Programme for Water Supply, Sanitation, and Hygiene.



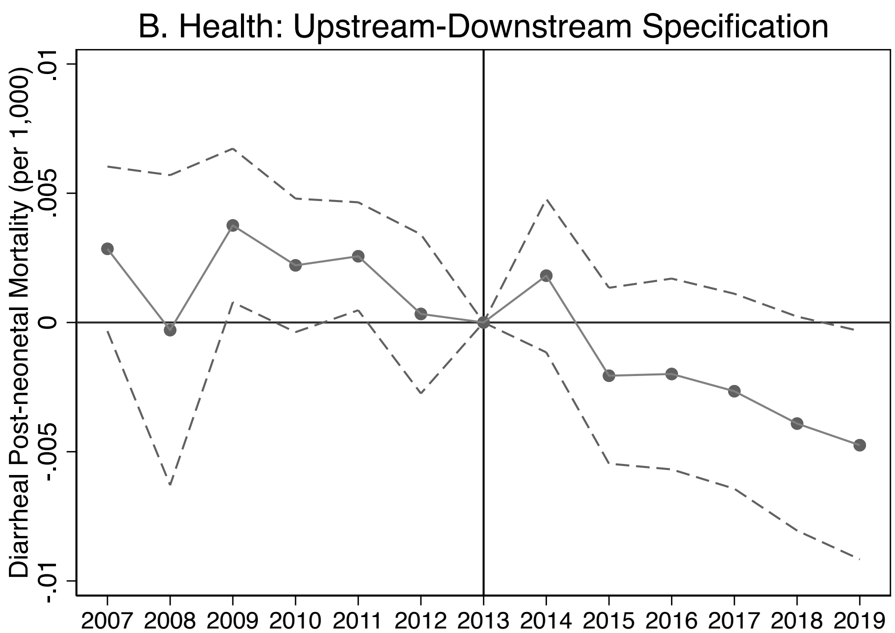


Figure A2: Event Study Plots of Reduced-Form Regressions of AWC in Upstream-Downstream Specification

Notes: This figure shows the regression coefficients of the logarithm of fecal coliform (Panel A) and diarrheal post-neonatal mortality per 1,000 people (Panels B) on the interaction terms between upstream AWC and year dummies. Both panels use the AWC of upstream districts within the range of $[0, 150]$ kilometers from a reference district. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the district level. Panel A includes monitoring station fixed effects, year fixed effects, and the following controls: precipitation and the interaction of AWC and post-SBM indicator of a reference district. Panel B includes district fixed effects, year fixed effects, and the following controls: precipitation and the interaction of AWC and post-SBM indicator of a reference district.

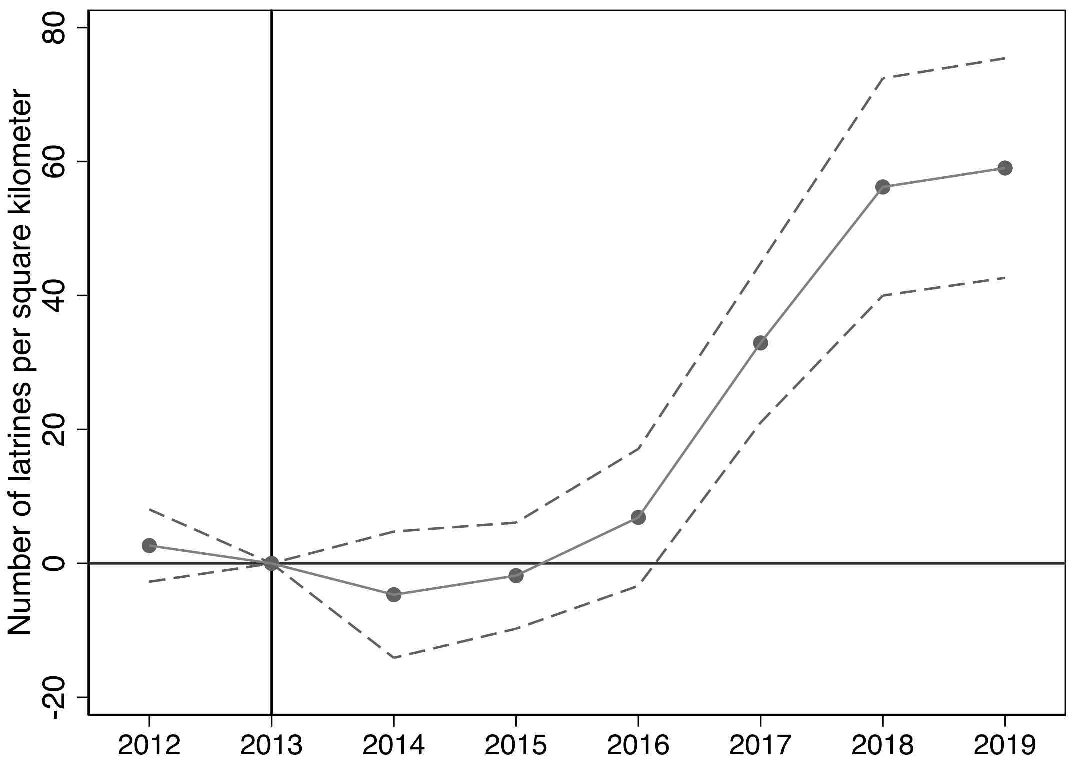


Figure A3: Differential Change in the Number of Latrines between Districts with Lower Baseline Coverage and Districts with Higher Baseline Coverage

Notes: This figure shows the regression coefficients of the number of latrines per square kilometer on the interaction terms between (1- baseline latrine coverage in 2013) and year dummies at the district level. The regression includes district fixed effects, year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the district level.

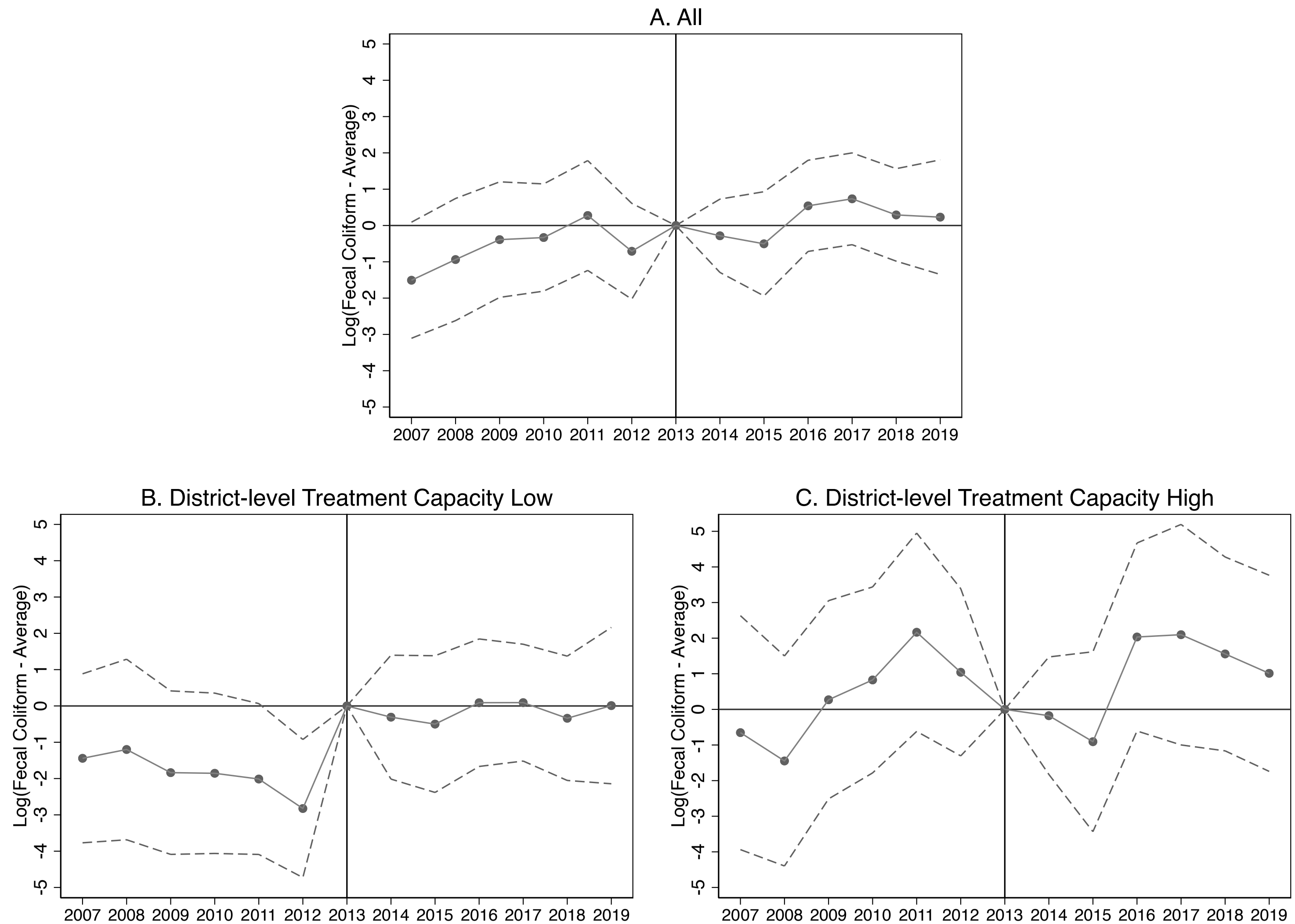


Figure A4: Heterogeneity in Dynamic Effects on Water Pollution (Log of Fecal Coliform) by District-level Treatment Capacities

Notes: This figure shows the regression coefficients of the logarithm of fecal coliform in equation 6. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the district level. All regressions include monitoring station fixed effects, basin-year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates.

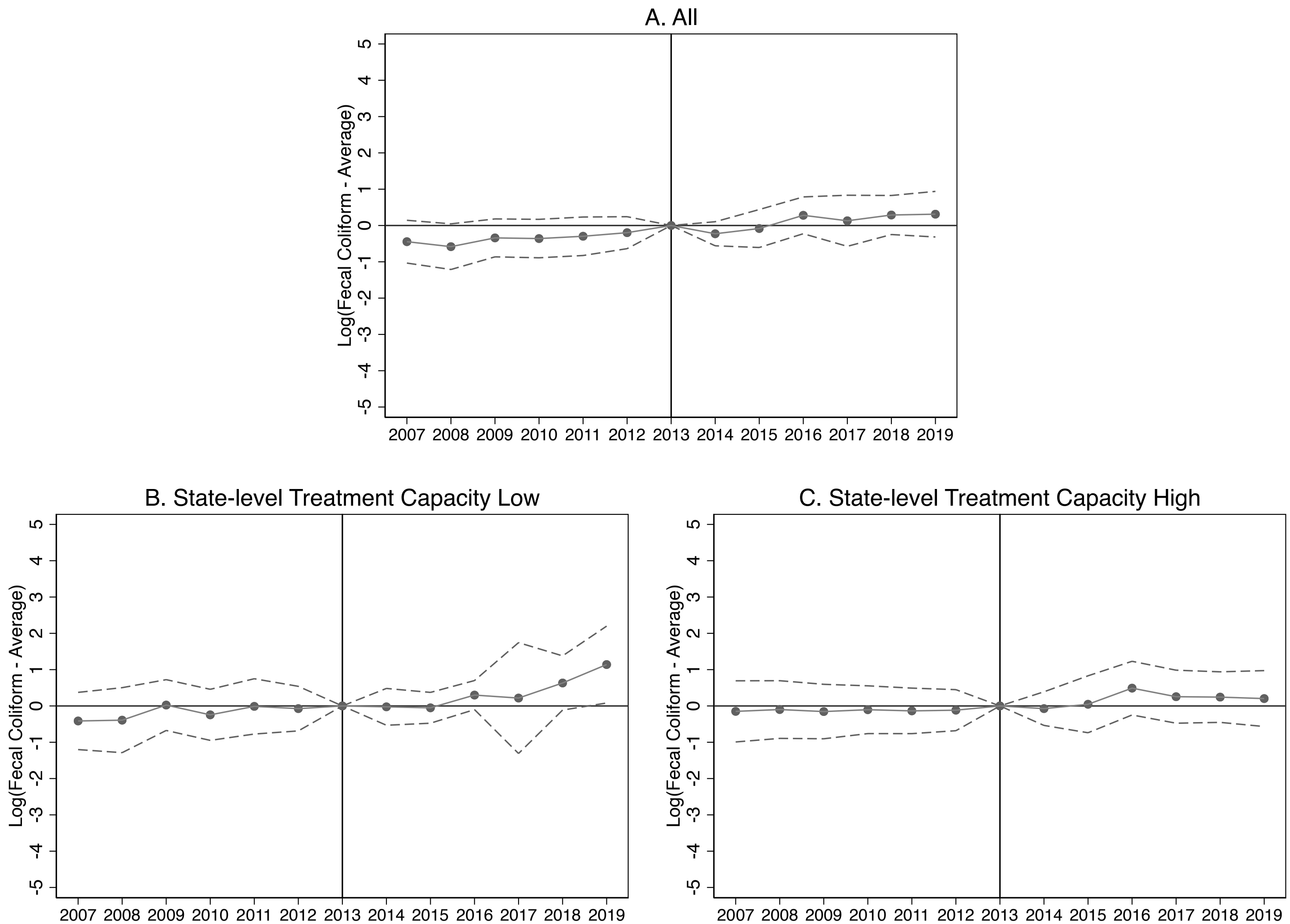


Figure A5: The Dynamic Effects on Water Pollution (Log of Fecal Coliform) in the Case of Binary Treatment

Notes: This figure shows the regression coefficients of the logarithm of fecal coliform in equation 6 when I adopt a binary treatment indicator that takes the value one when the district's latrine coverage is lower than the median. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the district level. All regressions include monitoring station fixed effects, basin-year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates.

B Additional Tables

Table B1: DID Results: The Effect on Water Quality (Log of Fecal Coliform) in the Case of Binary Treatment

	All	State-level Capacity		District-level Capacity	
	(1)	(2)	(3)	(4)	(5)
	All	High	Low	High	Low
2013 Latrine Coverage Low (= 1)	0.425^{**}	0.311	0.475^{**}	0.830	0.253
* Post (= 1)	(0.213)	(0.284)	(0.234)	(0.500)	(0.230)
Observations	10,385	5,075	5,281	4,240	6,110
R^2	0.860	0.869	0.882	0.882	0.878
Number of Stations	1,187	577	606	465	719
Number of Districts	335	182	151	95	238

Notes: This table reports the regression coefficients of the logarithm of fecal coliform in equation 5 when I change a continuous treatment measure to a binary treatment indicator that takes the value one when the district's latrine coverage is lower than the median. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All regressions include monitoring station fixed effects, basin-year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates. Column 2 reports a result in states where treatment capacities of sewage treatment plants are higher than the median, while Column 3 reports a result in states with lower treatment capacities. Similarly, Columns 4 and 5 compare results based on the different levels of treatment capacities at the district level.

Table B2: Upstream-Downstream Analysis: Alternative Buffer Sizes

	Buffer Distances from Reference Stations/Districts					
	(1)	(2)	(3)	(4)	(5)	(6)
	0-50km	0-100km	0-150km	50-150km	100-150km	Full
Panel A. Dependent Variable: Log(Fecal Coliform)						
Upstream number of	0.014	0.017	0.015	0.003	0.001	0.037**
latrines per sq. km	(0.012)	(0.013)	(0.011)	(0.009)	(0.007)	(0.016)
Observations	1,758	2,152	2,228	2,008	1,488	2,235
Number of Stations	287	352	365	325	238	367
Number of Districts	133	151	154	140	112	155
KP F-Stat	23.148	36.766	50.475	38.427	49.767	73.913
AR 95% CI	[-.011, .049]	[-.010, .048]	[-.008, .039]	[-.018, .021]	[-.019, .014]	[.005, .074]
Panel B. Dependent Variable: Diarrheal Post-neonatal Mortality (per 1,000 people)						
Upstream number of	-0.011*	-0.012*	-0.011*	-0.012*	-0.017***	0.003
latrines per sq. km	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)
Observations	688	808	824	704	488	840
Number of Districts	86	101	103	88	61	105
KP F-Stat	58.692	61.264	78.696	78.481	77.325	83.728
AR 95% CI	[-.026, .002]	[-.025, .001]	[-.023, .001]	[-.026, .001]	[-.030, -.004]	[-.014, .027]
Mean of Dep. Variable	2.695	2.571	2.576	2.763	3.078	2.570

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample is limited to monitoring stations (Panel A) and districts (Panel B) located along major rivers in India. In Columns 1-5, I change buffer sizes for identifying upstream districts. In Column 6, I include all upstream districts without the restriction on a buffer size. Panel A includes monitoring station fixed effects, year fixed effects, and the following controls: precipitation and the interaction of AWC and post-SBM indicator of a reference district. Panel B includes district fixed effects, year fixed effects, and the same controls as Panel A. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test.

Table B3: The Effects on Multiple Types of Diarrheal Mortality (per 1,000 people)

	(1) Early-neonatal	(2) Late-neonatal	(3) Post-neonatal	(4) Age 1-4	(5) Under 5
Number of latrines per sq. km	-0.240*** (0.040)	-0.108*** (0.018)	-0.029*** (0.005)	-0.006*** (0.001)	-0.013*** (0.002)
Observations	2,696	2,696	2,696	2,696	2,696
Number of Districts	337	337	337	337	337
KP F-Stat	39.248	39.248	39.248	39.248	39.248
AR 95% CI	[-.345, -.175]	[-.156, -.079]	[-.042, -.021]	[-.009, -.005]	[-.018, -.009]
Mean of Dep. Variable	16.428	7.663	2.282	0.365	0.859
Average Policy Effect	-6.800	-3.078	-0.827	-0.174	-0.355

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. All regressions include district fixed effects, year fixed effects, and precipitation as a control. The sample is limited to districts that have monitoring stations used in the specification of water quality. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer after the SBM started in 2014.

Table B4: Falsification Tests

	Log(Temperature)		Log(pH)		Log(BOD)		Log(Dissolved O2)		Log(Nitrate+Nitrite)		Malaria Mortality (%)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Number of latrines per sq. km	-0.0023		0.0001		-0.0034		-0.0008		0.0003		0.0000
	(0.0015)		(0.0005)		(0.0037)		(0.0010)		(0.0162)		(0.0001)
(1 - 2013 Latrine Coverage)		-0.0297		-0.0060		-0.1051		0.0448		-0.5631*	
* Post (= 1)		(0.0319)		(0.0117)		(0.1372)		(0.0368)		(0.3036)	
Observations	7,103	10,945	7,176	11,069	7,084	10,928	7,094	10,920	6,379	7,494	2,696
R^2	-	0.839	-	0.528	-	0.845	-	0.763	-	0.680	-
Number of Stations	1,179	1,185	1,189	1,187	1,184	1,185	1,181	1,180	1,142	1,149	-
Number of Districts	334	334	337	335	336	335	336	334	319	320	337
Identification	IV	DID	IV	DID	IV	DID	IV	DID	IV	DID	IV
KP F-Stat	28.358	-	29.240	-	28.067	-	29.955	-	7.991	-	39.248
AR 95% Cl	[-.005, .001]	-	[-.001, .001]	-	[-.011, .005]	-	[-.003, .001]	-	[..., .032]	-	[-.0002, .0003]

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The IV specification in Columns 1, 3, 5, 7, and 9 includes monitoring station fixed effects, year fixed effects, and precipitation as a control. The IV specification in Column 11 includes district fixed effects, year fixed effects, and precipitation as a control. The DID specification in Columns 2, 4, 6, 8, and 10 includes monitoring station fixed effects, basin-year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates. In Column 11, malaria mortality estimates for ages 0-4 are used. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. The open-ended confidence interval shows that the searched grids do not extend far enough to capture the point where the rejection probability crosses above the 95%.

Table B5: Robustness Check - Spillovers from Neighboring Districts: The Effect on Water Quality (Log of Fecal Coliform)

	All	State-level Capacity		District-level Capacity	
	(1)	(2)	(3)	(4)	(5)
	All	High	Low	High	Low
Panel A. IV Design					
Number of latrines per sq. km	0.027***	-0.027	0.037***	0.017*	0.043***
	(0.007)	(0.019)	(0.006)	(0.009)	(0.013)
Observations	7,253	3,605	3,648	3,300	3,953
Number of Stations	1,197	603	594	529	668
Number of Districts	489	260	229	185	304
KP F-Stat	44.626	14.440	54.539	26.013	15.433
AR 95% CI	[.013, .042]	[-.076, .010]	[.027, .050]	[-.003, .036]	[.021, .081]
Average Policy Effect	0.655	-0.599	0.952	0.362	1.140
Panel B. DID Design					
(1 - 2013 Latrine Coverage) * Post (= 1)	0.663	0.952	1.542**	0.699	1.573**
	(0.588)	(0.869)	(0.732)	(0.877)	(0.783)
Observations	10,464	5,131	5,285	4,850	5,573
R^2	0.862	0.863	0.897	0.878	0.887
Number of Stations	1,194	581	608	528	663
Number of Districts	487	244	238	184	300

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Panel A includes monitoring station fixed effects, year fixed effects, and precipitation as a control. Panel B includes monitoring station fixed effects, basin-year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates. Column 2 reports a result in states where treatment capacities of sewage treatment plants are higher than the median, while Column 3 reports a result in states with lower treatment capacities. Similarly, Columns 4 and 5 compare results based on the different levels of treatment capacities at the district level. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. The open-ended confidence interval shows that the searched grids do not extend far enough to capture the point where the rejection probability crosses above the 95%. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer after the SBM started in 2014.

Table B6: Robustness Check - Influence from Urban Areas

	No Exclusion	50km Exclusion	100km Exclusion	150km Exclusion
	(1)	(2)	(3)	(4)
Panel A. Dependent Variable: Log(Fecal Coliform) - IV Design				
Number of latrines	0.030***	0.039***	0.050***	0.072**
per sq. km	(0.008)	(0.010)	(0.015)	(0.035)
Observations	7,201	5,295	3,716	2,492
Number of Stations	1,189	890	623	421
Number of Districts	337	284	196	125
KP F-Stat	29.954	25.785	17.574	5.693
AR 95% CI	[.015, .049]	[.021, .067]	[.026, .099]	[.026, ...]
Average Policy Effect	0.719	1.035	1.369	1.902
Panel B. Dependent Variable: Diarrheal Post-neonatal Mortality (per 1,000 people)				
Number of latrines	-0.029***	-0.028***	-0.028***	-0.028***
per sq. km	(0.005)	(0.006)	(0.006)	(0.006)
Observations	2,696	1,512	1,512	1,512
Number of Districts	337	189	189	189
KP F-Stat	39.248	22.288	22.288	22.288
AR 95% CI	[-.042, -.021]	[-.049, -.019]	[-.049, -.019]	[-.049, -.019]
Mean of Dep. Variable	2.282	2.395	2.395	2.395
Average Policy Effect	-0.827	-0.824	-0.824	-0.824

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. In Columns 2-4, I exclude monitoring stations (Panel A) and districts (Panel B) that are within a specified distance from cities that have a population of 1 million and above. Panel A includes monitoring station fixed effects, year fixed effects, and precipitation as a control. Panel B includes district fixed effects, year fixed effects, and precipitation as a control. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer after the SBM started in 2014.

Table B7: Robustness Check - Balanced Panel: The Effect on Water Quality (Log of Fecal Coliform)

	All	State-level Capacity		District-level Capacity	
	(1)	(2)	(3)	(4)	(5)
	All	High	Low	High	Low
Panel A. IV Design					
Number of latrines	0.024***	-0.010	0.031***	0.009	0.039***
per sq. km	(0.009)	(0.022)	(0.008)	(0.012)	(0.014)
Observations	3,776	1,552	2,224	1,600	2,176
Number of Stations	472	194	278	200	272
Number of Districts	158	75	83	53	105
KP F-Stat	12.357	12.512	13.449	4.018	7.917
AR 95% CI	[.009, .048]	[-.072, .032]	[.018, .053]	[..., .048]	[.018, .086]
Average Policy Effect	0.644	-0.209	0.926	0.210	1.137
Panel B. DID Design					
(1 - 2013 Latrine	1.001	0.931	5.352***	2.993*	1.206
Coverage) * Post (= 1)	(0.781)	(1.146)	(1.380)	(1.616)	(1.000)
Observations	3,433	1,625	1,781	1,572	1,847
R^2	0.838	0.877	0.867	0.879	0.841
Number of Stations	276	130	144	126	149
Number of Districts	145	70	73	57	87

Notes: The coefficients are reported. Standard errors, clustered at the district level, are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The sample is limited to monitoring stations that have observations every year from 2012 to 2019, which yields a balanced panel. Panel A includes monitoring station fixed effects, year fixed effects, and precipitation as a control. Panel B includes monitoring station fixed effects, basin-year fixed effects, and the following controls: precipitation, VIIRS nighttime luminosity, population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates. Column 2 reports a result in states where treatment capacities of sewage treatment plants are higher than the median, while Column 3 reports a result in states with lower treatment capacities. Similarly, Columns 4 and 5 compare results based on the different levels of treatment capacities at the district level. The KP F-Stat refers to the Wald version of the Kleibergen and Paap (2006) rk-statistic on the excluded instrumental variables for non-i.i.d. errors. The AR 95% CI reports the 95% confidence interval, which is robust to the weak instrument based on the Anderson and Rubin (1949) test. The open-ended confidence interval shows that the searched grids do not extend far enough to capture the point where the rejection probability crosses above the 95%. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer after the SBM started in 2014.

C Data Appendix

C.1 Water Quality

- I obtain the station-level water quality data of rivers from the following data sources.
    1. 2012-2019: NWMP (National Water Quality Monitoring Programme) Data, Central Pollution Control Board
       `https://cpcb.nic.in/nwmp-data/` (accessed January 15, 2021)
    2. 2007-2011: Water Quality Database, National Water Quality Monitoring
       `http://www.cpcbenvis.nic.in/water_quality_data.html` (accessed January 15, 2021)
- These datasets are separated by types of water bodies: (i) rivers, (ii) medium and minor rivers, (iii) canals, seawater, drains, STPs (sewage treatment plants), and WTPs (water treatment plants), (iv) lakes, ponds, and tanks, and (v) groundwater. In this paper, I use the data from the first type (rivers).
- I use the yearly average values of the following water quality indicators in the analysis (2-6 for falsification tests).
    1. Fecal Coliform
    2. Temperature
    3. pH
    4. Dissolved Oxygen
    5. BOD
    6. Nitrate and Nitrite
- I complement these datasets with the GPS location data of water quality monitoring stations in the following document.
    - Central Pollution Control Board Website
      `https://cpcb.nic.in/wqm/WQMN_list.pdf` (accessed January 15, 2021)
- I use 2011 district-level boundary data and GPS location data of monitoring stations to identify districts where monitoring stations are located. Thus, identified districts are based on the 2011 boundary.

C.2 Health

- I obtain the 5-kilometer raster data of mortality estimates from 2000 to 2019 from the following data sources.

1. Diarrheal mortality: Global Under-5 Diarrhea Incidence, Prevalence, and Mortality Geospatial Estimates 2000-2019, Institute for Health Metrics and Evaluation (IHME, 2020b)
   `https://ghdx.healthdata.org/record/ihme-data/global-under-5-diarrhea-incidence-prevalence-mortality-geospatial-estimates-2000-2019` (accessed May 30, 2021)
2. Malaria Mortality: Global Malaria Incidence, Prevalence, and Mortality Geospatial Estimates 2000-2019, Institute for Health Metrics and Evaluation (IHME, 2020a)
   `https://ghdx.healthdata.org/record/ihme-data/global-malaria-incidence-prevalence-mortality-geospatial-estimates-2000-2019` (accessed May 29, 2022)

- These estimates are computed by applying the Bayesian model-based geostatistical framework to the data in the following household surveys and databases.
  - Diarrheal mortality: India Demographic and Health Survey 2005-2006, 2015-2016, the India District Level Household Survey 2002-2005, 2007-2008, 2012-2014, and the India Human Development Survey 2004-2005, 2011-2013
  - Malaria Mortality: India Demographic and Health Survey 2005-2006, 2015-2016, Malaria Atlas Project Plasmodium Falciparum Parasite Rate Database, Malaria Atlas Project Annual Parasite Incidence Database
- I use estimates of diarrheal mortality of five age groups, i.e., early-neonatal (0-6 days), late-neonatal (7-27 days), post-neonatal (28-364 days), ages 1-4, and under age 5. I also use the estimates of malaria mortality for ages 0-4, which is the closest age group to that in diarrheal mortality.
- I use the mean estimates of mortality, although lower-bound (2.5% percentile) and upper-bound (97.5% percentile) estimates are also available.
- For the analysis, I compute the district-level mean of mortality estimates based on this raster data and 2011 district-level boundary data.

C.3 Latrines

- I obtain data on the number of constructed household latrines from 2012 to 2019 in rural India from the following database.
  - Format A03: Swachh Bharat Mission Target Vs Achievement On the Basis of Detail entered, Swachh Bharat Mission - Gramin (All India)

https://sbm.gov.in/sbmReport/Report/Physical/SBM_TargetVsAchievementWithout1314.aspx (accessed March 28, 2020)

- The raw tables scraped from this website record numbers of constructed latrines at the village level, so I aggregate them to the district-level data for analysis.
- This dataset uses district names in 2019, so I transform the data to follow the 2011 boundary by considering district splits from 2011 to 2019. For example, if district A split into districts B and C between 2011 and 2019, I compute the number of latrines in district A as the total number of latrines in districts B and C. This aggregation allows me to match latrine data with water quality data based on the 2011 boundary.
- For the IV specification, I compute the number of latrines per square kilometer by dividing the number of latrines by district area. The district area is computed from the 2011 district boundary data.
- For the DID specification, I compute the latrine coverage in 2013 by dividing the number of latrines in 2013 by the total number of recorded households in each district.

C.4 GIS (Geographic Information System) Data

- 2011 District Boundary
  - I obtain the shape files of the 2011 district boundary of the ML Infomap from the Data Lab at Tufts University.
  - This dataset includes 640 districts that were available in India in 2011.
  - I use this boundary data to match all datasets used in the analysis.
- River Basin
  - I obtain the shape files of the "Watershed Map of India" of the ML Infomap from the Data Lab at Tufts University.
  - This dataset records the boundaries of 34 river basins in India.
  - I use this basin data to identify the basin of each monitoring station.
- River Line 1
  - I obtain polygons of rivers from the following data source.
    - The version 4.1.0 GIS polygons of rivers and lakes (1:10m), Natural Earth https://www.naturalearthdata.com/downloads/10m-physical-vectors/10m-rivers-lake-centerlines/ (accessed April 15, 2021)
  - This dataset covers 43 major rivers in India.

- I use this dataset of river lines for identifying upstream and downstream districts.

- River Line 2
  - I obtain polygons of rivers from the following data source.
    * Global River Widths from Landsat (GRWL) Database (Allen and Pavelsky, 2018)
      `https://zenodo.org/record/1297434` (accessed April 16, 2021)
  - This dataset covers rivers that are ≥30-meter wide at mean annual discharge globally.
  - I use this river line data for measuring the exposure to river pollution.
- Digital Elevation Data
  - I obtain 90-meter raster elevation data from the following database.
    * Shuttle Radar Topography Mission (SRTM) data Version 4.1, International Centre for Tropical Agriculture (Reuter et al., 2007)
      `https://cgiarcsi.community/data/srtm-90m-digital-elevation-database-v4-1/` (accessed May 3, 2021)
  - I use this elevation data for identifying upstream and downstream districts.

C.5 Available Water Capacity

- I obtain the 30 arc-second raster data of Available Water Capacity from the following data source.
  - Harmonized World Soil Database v1.2, Food and Agriculture Organization of the United Nations (FAO)
    `https://www.fao.org/soils-portal/soil-survey/soil-maps-and-databases/harmonized-world-soil-database-v12/ru/` (accessed July 22, 2021)
- For the analysis, I compute the district-level mean of Available Water Capacity based on this raster data and 2011 district-level boundary data.

C.6 Sewage Treatment Plants (STPs)

- I obtain an inventory of STPs from the following data source.
  - Inventorization of Sewage Treatment Plants, Central Pollution Control Board (CPCB, 2015)
    `https://nrcd.nic.in/writereaddata/FileUpload/NewItem_210_Inventorization_of_Sewage-Treatment_Plant.pdf` (accessed April 12, 2021)

- This dataset includes detailed information on 816 STPs in 28 states and union territories in India in 2015.
- I first extracted 467 STPs that were operational in 2013 and had information on the installed capacity.
- Next, I manually assign state and district names to these STPs based on their city/town locations.
- Lastly, I calculate the aggregated STP capacities at both state and district levels in 2013 for the analysis.

C.7 Other District Characteristics

- Precipitation
  - I obtain 0.25-degree raster data of precipitation from 2007 to 2019 from the following data source.
    * Gridded Rainfall (0.25 x 0.25) NetCDF File, India Meteorological Department (Pai et al., 2014)
      `https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html` (accessed April 8, 2021)
  - First, I aggregate daily raw data to annual data.
  - Then, for the analysis, I compute the district-level mean of annual precipitation based on this raster data and 2011 district-level boundary data.
- Nighttime Light
  - I obtain 15 arc second raster data of nighttime light in 2013 from the following data source.
    * V.2 annual composites of Visible and Infrared Imaging Suite (VIIRS) Day Night Band (DNB), Earth Observation Group, National Oceanic and Atmospheric Administration (Elvidge et al., 2021)
      `https://eogdata.mines.edu/products/vnl/` (accessed April 20, 2021)
  - Specifically, I use the values of masked average radiance, which represent stable lights from which background noises, biomass burning, and aurora are removed.
  - For the analysis, I compute the district-level mean of nighttime luminosity in 2013 based on the annual composite of 2013 and 2011 district-level boundary data.
- Other Socio-demographic Characteristics

- I obtain district-level data on population, the proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates of rural India in 2011 from the 2011 Census of India.
    * Basic Population Figures of India/State/District/Sub-District/Village, 2011 Census
      `https://censusindia.gov.in/nada/index.php/catalog/42560` (accessed May 30, 2022)

C.8 Identification of Upstream and Downstream Districts

- I identify upstream and downstream districts for the upstream-downstream analysis, which is discussed in Section 5.3.
- I first focus on districts located along 43 major rivers in the GIS polygons of the Natural Earth. Some of the districts are further dropped if they have no further upstream and downstream districts. Then, I use 158 districts located along those major rivers, while the baseline specification uses 337 districts. For the water quality data, I use 365 monitoring stations that are within 4km of the major rivers, while the baseline specification uses 1,189 stations.
- Second, I use elevation data along those rivers to identify the upstream-downstream relationships among monitoring stations and districts. The upstream districts of a given district (station) are selected as the districts that intersect with river segments whose elevations are higher than the elevation of the given district (station).
- If two or more rivers flow through a given district, I do not include this given district in the final sample because the upstream-downstream relationships are unclear. 82 districts are dropped from the sample in this process.
- I adopt a variety of distances from a given district (station) for identifying upstream districts. Specifically, for a given district (station), the upstream districts are selected from districts that fall within a range of $[X, Y]$ kilometers from the given district (station), where $X \in \{0, 50, 100\}$, $Y \in \{100, 150\}$, and $X < Y$.
- The same procedure is repeated to identify downstream districts. These districts are selected as the districts that intersect with river segments whose elevations are lower than the elevation of the given district (station).

C.9 Identification of Neighboring Districts

- I identify neighboring districts for the robustness check of considering the spillovers from neighboring districts, which is discussed in Section 6.4.

- First, I identify monitoring stations that are situated in more than one district. I create 2-kilometer buffers around stations and select stations whose buffers include more than one district.
- Out of 1,189 monitoring stations, 324, 26, and 1 monitoring station(s) are situated among two, three, and four districts, respectively.
- Then, for these identified monitoring stations, I compute the weighted average of variables of neighboring districts by using district areas as weights.
- The data of other monitoring stations remain unchanged.

C.10 Identification of Urban Areas

- I identify urban areas for the robustness check of excluding the influence of urban areas, which is discussed in Section 6.4.
- First, I focus on 53 urban agglomerations/cities that have a population of 1 million and above in 2011. These cities are identified from the following data source of the 2011 Census.
  - `https://web.archive.org/web/20111113152754/http://www.censusindia.gov.in/2011-prov-results/paper2/data_files/India2/Table_3_PR_UA_Citiees_1Lakh_and_Above.pdf` (accessed March 7, 2022)
- Second, I obtain the GPS locations of these cities by using the GeoNames geographical database (`http://www.geonames.org/about.html`).
- Third, I construct urban areas that are within 50/100/150 kilometers from the GPS locations of these cities.
- Finally, I exclude monitoring stations and districts that are located within these urban areas as a robustness check.