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

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Abstract

Developing countries have increased sanitation investment to improve child health. However, scaling up latrine construction can cause water pollution externalities owing to insufficient infrastructure for the treatment of fecal sludge, offsetting the direct health benefits. I estimate the negative externalities of an Indian sanitation policy that subsidized the construction of over 100 million latrines. Exploiting geographical variations in soil characteristics that affect the feasibility of latrine construction, I find that this policy increases fecal contamination of rivers by 72%. Although the policy reduces diarrheal child mortality overall, this positive health effect is eliminated when upstream areas lack adequate wastewater infrastructure.

JEL: I15, O13, Q53, Q56

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1 Introduction

Policymakers and researchers have recognized the importance of sanitation investments in improving child health in developing countries. Poor access to sanitation facilities and the associated practice of open defecation increase the risk of diarrheal diseases and mortality, adversely affecting child health. Worldwide, according to WHO/UNICEF data, 688 million people practiced open defecation in 2016, leading to 432,000 deaths (Prüss-Ustün et al., 2019). Consequently, developing countries such as India and China have adopted nationwide policies that subsidize the construction of latrines (toilets).[1] These policies are intended to reduce open defecation and exposure to fecal matter near human habitats, thereby improving child health. These direct health benefits have been well-documented as local impacts at the village level (e.g., Geruso and Spears, 2018; Cameron et al., 2021, 2022).

However, the negative externalities of scaling up latrine construction as a nationwide policy remain unclear and can offset its direct health benefits. The constructed latrines accumulate a large volume of fecal sludge, which requires periodic emptying using vacuum trucks or manually. Subsequently, the emptied fecal sludge should be treated by infrastructure, specifically wastewater treatment plants, to destroy the remaining active pathogens. However, owing to insufficient infrastructure, a growing volume of fecal sludge, exacerbated by the intensive increase in latrine construction under the policy, may be directly dumped into rivers, thus polluting them. These water pollution externalities can decrease the overall effectiveness of latrine construction in improving child health. In extreme cases, latrine construction can worsen health outcomes if the water pollution externalities exceed the direct positive effects of reduced open defecation.

Therefore, I examine the 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 approximately USD 6 billion to subsidize the construction of over 100 million latrines at the household level in rural India.[2] The impact of the SBM deserves careful examination as it is the largest sanitation policy in the world. I use administrative panel datasets on the district-level number of household latrines from 2012 to 2019 under the SBM and the water quality of 1,189 monitoring stations along rivers in 337 districts from 2007 to 2019 to examine the negative externality of water quality. I combine these data with district-level panel data on diarrheal child mortality rates

[1] Like the Indian government's Swachh Bharat Mission examined in this paper, under the "Toilet Revolution," the Chinese government built and upgraded over 10 million rural toilets in 2018.

[2] The types of latrines most commonly used in rural India are pit latrines and latrines with septic tanks. Because these are not connected to sewer pipes, they accumulate fecal sludge. The disposal of fecal sludge from these latrines can result in water pollution externalities.

to examine the effects on health.

This analysis captures the differential effects of latrine construction relative to open defecation, which can also cause water pollution externalities. Open defecation, which is practiced before latrine construction, generates small amounts of stool across a wide range of locations. These stools are flushed into rivers only if it rains and if open defecation sites are close to rivers. Conversely, the constructed latrines contain a large concentration of fecal sludge that may be dumped directly into rivers. Thus, the volume of fecal sludge that reaches rivers may increase after latrine construction, causing increased water pollution.

To identify the causal effects of latrine construction on water quality and health, I adopt an instrumental variable (IV) design that exploits geographical variations in soil characteristics that affect the feasibility of latrine construction under the SBM. Specifically, I use Available Water Capacity (AWC), a proxy for the soil infiltration rate, interacted with a post-SBM indicator, as an instrument for the number of latrines.[3] This IV design is conceptually similar to the difference-in-differences (DiD) design, in which the reduced-form regression uses AWC as a treatment variable. Higher infiltration rates (lower AWC) increase the risk of groundwater contamination in wells from fecal sludge accumulated in the latrines. To address this risk, an official technical guideline (CPHEEO, 2013), which has become effective since the SBM's inception in 2014, requires either greater distances between latrines and wells or the addition of impervious materials inside latrines in areas with high infiltration rates. Therefore, a lower AWC increased the difficulty and cost of latrine construction after the SBM started in 2014. Indeed, a lower AWC was associated with a smaller increase in latrines during the post-SBM period in the first stage.

I also adopt an upstream–downstream specification that examines the effects of upstream latrine construction on downstream water quality and health. Dumped fecal sludge from latrines can flow downstream along rivers, causing water pollution externalities in downstream areas. I test these spillover effects in the modified IV design, where I use the upstream AWC as an instrument for upstream latrine construction and examine its impact on downstream outcomes. This upstream–downstream specification addresses the concern of exclusion restrictions in the baseline IV design, especially for health outcomes. One potential violation could be that AWC, which measures soil quality, affects health outcomes in the same area by influencing agricultural output and income, which, in turn, affects the level of health investments. However, upstream AWC is not expected to affect downstream health outcomes through this income channel, because upstream AWC is unlikely to be associated with downstream agricultural output and income. Indeed, in the reduced-form event study regressions,

[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.

I find that upstream AWC did not have differential effects on water quality and health prior to the SBM policy (before the official technical guideline was published), supporting the validity of the exclusion restriction.[4]

My results show that latrine construction under the SBM degrades river water quality while improving overall health. I find that one additional latrine per square kilometer increases fecal coliform in rivers by 3%. The total effect of the SBM is estimated to be a 72% increase in river pollution. Moreover, the upstream–downstream specification shows that water pollution externalities spill over to downstream areas, especially several years after the SBM started. However, additional upstream latrine construction per square kilometer reduces the downstream diarrheal post-neonatal mortality rate per 1,000 children by 0.011, which is a 0.4% reduction from the pre-SBM period. The total health effect of the SBM is estimated to be a 10% decrease in diarrheal post-neonatal mortality rate. This overall positive health effect suggests that the direct positive health effect of decreased open defecation outweighs the negative externality on health due to increased water pollution.

To explore the mechanisms behind these negative externalities, I examine whether the effects on water quality vary by the level of complementary infrastructure for fecal sludge treatment. Sufficient infrastructure for treating wastewater can prevent the dumping of fecal sludge from latrines, which is the main mechanism of negative externalities. The most common infrastructure in India is sewage treatment plants (STPs), which co-treat urban sewage and rural fecal sludge. Therefore, I compare the effects between areas with higher and lower treatment capacities of STPs than the median. In both the baseline and upstream–downstream specifications, the negative externality of water quality is eliminated in areas with higher treatment capacities. Conversely, in areas with lower treatment capacities, the negative externality of water quality is significant and spills over downstream, suggesting that dumping of untreated fecal sludge is the mechanism.

The same heterogeneity analysis by the treatment capacity of fecal sludge for the health outcome suggests that water pollution externalities offset the direct positive health effects. The total effect of the SBM is a 15% (42%) decrease in diarrheal post-neonatal mortality rate when upstream districts (states) have higher treatment capacities, coupled with insignificant water pollution externalities. However, the positive health effect is eliminated in cases with lower upstream treatment capacities when water pollution externalities are significant. These heterogeneous health effects suggest that water pollution externalities offset the direct positive health effects, thereby reducing the overall effectiveness of latrine construction in

[4] For the water quality outcome, I do not find differential effects of AWC prior to the SBM policy in either the baseline or the upstream–downstream specification. Therefore, I present results for both specifications for the water quality outcome, while I focus on the upstream–downstream results for the health outcome.

improving child health in rural India.

A variety of tests corroborate my findings on the negative externalities of latrine constructions. First, falsification tests show no effects on unrelated water quality and health outcomes, strengthening the validity of the exclusion restriction. Second, the results are robust to an alternative DiD design, consideration of spillovers from neighboring districts and urban areas, and adoption of a balanced panel and alternative mortality dataset.

My findings suggest that an enabling environment that includes effective infrastructure for the treatment of fecal sludge can make sanitation policies more effective. The back-of-the-envelope cost–benefit analysis at the district level shows that the net mortality benefit (USD 5.6 million) is approximately one-third of the subsidy cost of the SBM policy (USD 16.9 million). However, complementing latrine construction with higher treatment capacities to mitigate negative externalities would substantially increase the mortality benefit (by USD 7.4 million) with lower additional construction and operating costs for more STPs (USD 4.5 million). These findings highlight the importance of incentivizing private goods together with complementary public goods to prevent potential negative externalities.

This paper makes three main contributions to the literature. First, it contributes to the literature on the effects of sanitation interventions by revealing the negative externalities of toilet construction on the environment and health. Previous studies have thus far focused on the direct positive effects of sanitation interventions on child health and mortality (Duflo et al., 2015; Hammer and Spears, 2016; Coffey et al., 2018; Geruso and Spears, 2018; Spears, 2018; Alsan and Goldin, 2019; Cameron et al., 2019, 2021, 2022; Flynn and Marcus, 2023).[5] I complement these findings by showing that toilet construction causes unintended water pollution externalities that offset the direct positive health effects. My analysis leveraging policy variation across hundreds of districts in India allows me to examine negative externalities that can extend beyond villages, which have not been captured in most previous studies that relied on village-level field experiments. Moreover, this paper provides new evidence on the impacts of the SBM policy, which is the world's largest toilet construction program.

Second, this paper contributes to the literature on the causes and effects of water pollution by providing the first causal estimate of the effect of toilet construction on river water quality.[6] Previous studies examined how water quality is affected by regulations (Greenstone

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

[6] 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). This paper estimates

and Hanna, 2014; Keiser and Shapiro, 2019), political boundaries (Lipscomb and Mobarak, 2016; Motohashi and Toya, 2024) and court rulings (Do et al., 2018; Bhupatiraju et al., 2024). Another set of studies investigated the effects of industrial and agricultural wastewater on health outcomes, including digestive cancer (Ebenstein, 2012), infant mortality (Brainerd and Menon, 2014; Mettetal, 2019), and birth outcomes (Dias et al., 2023). This paper shows that toilet construction can also substantially increase river pollution (by 72% under the SBM, which is a large effect), and that this increase in domestic wastewater can offset the positive health effects. While a related concurrent paper, Lepault (2024), examines the positive impacts of urban sewage treatment plants on water quality and child health, this paper sheds light on the negative pollution effects of rural toilet construction, which have adverse health implications.

Third, and more broadly, this paper advances the literature on the unintended negative effects of health policies in developing countries by showing that the negative effects of the displacement of pollution sources can be minimized with sufficient complementary infrastructure. Previous literature has documented how health policies can worsen health outcomes due to reduced complementary health behaviors (Bennett, 2012), switching to alternative unsafe health behaviors (Buchmann et al., 2019), abandonment and delays in project completion (Bancalari, 2024). This paper shows that unintended negative effects can also be caused by the displacement of pollution sources from open defecation sites to rivers where emptied fecal sludge is dumped. I then demonstrate that these effects can be mitigated by complementary infrastructure for pollution control.[7]

The remainder of this paper is organized as follows. Section 2 describes the SBM and its potential effects on water quality and health. Sections 3 and 4 describe my data and empirical strategies, respectively. Section 5 presents the baseline results of the effects on water quality and health. Section 6 presents the heterogeneous effects of latrine construction. Finally, Section 7 concludes the paper.

2 Background

2.1 Latrine Construction under Swachh Bharat Mission in India

To eliminate open defecation, the Indian government subsidized the construction of over 100 million latrines in rural India under the SBM, the largest sanitation policy in the world.

the causal effect of latrines on river water quality based on nationwide administrative data.

[7] Relatedly, my findings underscore the importance of public capacity to cope with the increased consumer demand under demand-side incentives, as also observed in other contexts like healthcare (Andrew and Vera-Hernández, 2024).

In India, many people have historically practiced open defecation, which increases the risk of diarrheal diseases and mortality, adversely affecting child health. About 470 million people in India practiced open defecation in 2013, according to the WHO/UNICEF Joint Monitoring Programme. As such, India had the highest number of people practicing open defecation in the world, more than ten times that of the country with the second-highest number, Nigeria, in 2013 (Appendix Figure E1).

To eliminate open defecation, the Indian government implemented a nationwide sanitation policy, the SBM, that subsidized household latrine construction in rural areas.[8] Since its inception in 2014, the SBM has set the ambitious goal of achieving universal latrine coverage by October 2, 2019, the 150th anniversary of Mahatma Gandhi's birth. To achieve this goal, SBM substantially increased the subsidy to a maximum of INR 12,000 (approximately USD 140) per household, covering most of the initial costs of basic latrines in rural India.

With this big push to construct latrines, SBM has become the world's largest sanitation policy, with central government expenditures totaling nearly USD 6 billion from 2014 to 2019, during which the number of rural households with latrines increased by 100 million.[9] According to the administrative database of the SBM, latrine coverage dramatically increased from 39.2% in 2013 to almost 100% in 2019 (Figure 1). Although the latrine coverage calculated from the administrative database is likely overestimated, recent independent surveys corroborate a substantial improvement in latrine coverage. For example, the National Annual Rural Sanitation Survey, conducted by an independent verification agency with support from the World Bank, found that 85% of the rural population used latrines in 2019–2020 (IVA, 2020).[10] As the largest sanitation policy in the world, the impact of the SBM on water quality and health requires careful examination.[11]

2.2 Negative Externality of Latrine Construction on Water Quality

Scaled-up latrine construction under the SBM may cause an unintended negative externality in river water quality owing to the insufficient treatment of fecal sludge.

Dumping fecal sludge emptied from constructed latrines can cause river pollution. La-

[8] SBM is the most recent policy out of four consecutive sanitation policies at the central government level. Although state governments have primary responsibility for sanitation, these central policies were meant to influence the state-level sanitation efforts through policy guidance and budget allocation.

[9] The annual budgets of the Indian government show that the central government spent USD 5.96 billion (INR 497 billion) from 2014 to 2019. The data source of the number of latrines built is the SBM website at `https://swachhbharatmission.gov.in/SBMCMS/about-us.htm`.

[10] The National Family Health Survey 5 also reported that 74.1% of households in rural India used toilets or latrines without practicing open defecation in 2019–2021.

[11] This paper focuses on examining the impacts of household-level latrine construction in rural areas, as promoted under the SBM-Gramin, in contrast to the construction of school-level latrines in rural areas (Adukia, 2017) or public toilets that are more prevalent in urban areas.

trines accumulate a large volume of fecal sludge, which requires periodic emptying using private services such as vacuum trucks or manual emptying services. Subsequently, the emptied fecal sludge should be transported to and treated at wastewater treatment plants to destroy the remaining active pathogens.[12] However, owing to insufficient infrastructure, a growing volume of fecal sludge, exacerbated by the intensive increase in latrine construction under the SBM, may be directly dumped into rivers, thus polluting them.[13]

My analysis captures the differential effects of latrine construction relative to open defecation that can also cause water pollution externality. Open defecation, which is practiced before latrine construction, generates small amounts of stool across a wide range of locations. These stools are flushed into rivers only if it rains and if open defecation sites are close to rivers. Conversely, 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 increase after latrine construction, causing increased water pollution.

I argue that the water pollution externality of latrine construction is unintended, as evidenced by the absence of policy targets for the treatment of fecal sludge. According to a SBM guideline (MDWS, 2018), the open-defecation-free status of a village is declared and verified based on a checklist of multiple indicators, including access to toilet facilities, 100% usage, fly-proofing, and safe septage disposal. In the safe septage disposal section, although the checklist stipulates that toilets should be connected to pits or septic tanks, it lacks specific guidance on how emptied fecal sludge should be treated properly.

2.3 Negative Externality of Latrine Construction on Health

Latrine construction under SBM may also result in a negative externality to health through exposure to increased river pollution. This water pollution externality may offset the positive health effects of reduced open defecation.

My analysis investigates the overall health effect determined by the magnitudes of both the direct positive health effects and the indirect negative externality of latrine construction. On the one hand, latrine construction has direct positive health effects by reducing open defecation and exposure to fecal matter near human habitats, leading to a reduction in diar-

[12] 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).

[13] The practice of dumping fecal sludge is highlighted in an ethnographic study on 32 truck operators who desludge latrines, although this study focuses on urban areas in Bangalore, Karnataka (Prasad and Ray, 2019). Additionally, several news media reports have highlighted the dumping of fecal sludge and the associated water pollution owing to insufficient wastewater infrastructure (e.g., DownToEarth (`https://www.downtoearth.org.in/news/waste/pollution-time-bomb-ticking-for-ganga-despite-odf-63790`)).

rheal diseases and mortality among children. Conversely, latrine construction can indirectly harm health by causing water pollution externalities. Exposure to polluted water from activities such as drinking river water and bathing in rivers can increase the risk of diarrheal diseases and mortality among children (Moe et al., 1991; Garg et al., 2018; Buchmann et al., 2019). Thus, the water pollution externalities of latrine construction may offset the direct positive health effects of reduced open defecation. This tradeoff is formally presented in the conceptual framework in Appendix A.

2.4 Complementary Infrastructure for Treatment of Fecal Sludge

The magnitude of the negative externalities of latrine construction is expected to vary by the level of complementary infrastructure for fecal sludge treatment. Adequate infrastructure for fecal sludge treatment can prevent the dumping of emptied fecal sludge, which is the main mechanism behind the negative externalities of latrine construction.

In India, local governments are tasked with developing wastewater infrastructure, such as STPs and fecal sludge treatment plants (FSTPs), to treat fecal sludge emptied from latrines.[14] STPs are large-scale infrastructure that has been available in India for many years. India had approximately 500 operating STPs in 2015 (CPCB, 2015). STPs are typically designed to treat urban sewage, but they are also increasingly used to co-treat fecal sludge owing to the underutilization of STP capacities in India.[15] FSTPs are newly developed, small-scale facilities for the treatment of fecal sludge. FSTPs began operating in 2014, and approximately 30 FSTPs were in operation at the end of 2019 (Rao et al., 2020).

I use geographical variations in STP capacity in the pre-SBM period to examine the heterogeneous effects on water quality and health.[16] The negative externality of water quality is expected to be substantial in areas with lower treatment capacity. In these areas, the negative externality of health through pollution exposure is expected to be greater, suggesting a smaller overall positive health effect. Conversely, I expect to find smaller water pollution externalities in areas with high treatment capacities, leading to larger positive health effects. I develop a conceptual framework in Appendix A to derive these predictions for heterogeneous effects, which are tested in Section 6.

[14] Wastewater infrastructure is used to treat fecal sludge from both pit latrines and latrines with septic tanks in rural areas, whereas in urban areas, it is used to treat sewage from sewer networks.

[15] 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 stipulating the co-treatments at STPs have been formulated by the central government and multiple states, including Punjab, Madhya Pradesh, Jharkhand, and Rajasthan (Gupta et al., 2018).

[16] I do not consider FSTP capacities because there were no FSTPs in the pre-SBM period.

3 Data

I combine administrative datasets on river water quality and household latrines across India to examine the negative externality of latrine construction on water quality. I use diarrheal child mortality estimates as an additional outcome to examine the negative externality to health. I also use AWC as an instrument for latrine construction. These data are spatially matched based on 2011 district boundary data.[17]

3.1 Water Quality

I adopt two outcome variables in this paper: water quality and health. First, I use yearly water quality data from 1,189 monitoring stations along the rivers in India from 2007 to 2019 (Figure 2). The yearly data are provided based on the monthly or quarterly monitoring of water quality as part of the National Water Quality Monitoring Programme (NWMP) managed by the Central Pollution Control Board (CPCB).

Among multiple water quality indicators, I use fecal coliform as the main indicator because it is a direct measurement of fecal contamination caused by fecal sludge emptied from latrines.[18] A higher number of fecal coliforms indicates a higher level of fecal contamination. The baseline analysis uses the average of the yearly maximum and minimum values of fecal coliform, although I also use the maximum values for the robustness check, as they may be more relevant to health impacts.[19] Since the distribution of fecal coliform is right-skewed and approximately log-normal, I use the logarithm of fecal coliform as a water quality outcome in the analysis.[20] Moreover, because fecal coliform values can be extremely high, as shown in Table 1, I conduct a robustness check by running the analysis after removing outliers above the 99th, 95th, 90th, and 75th percentiles.[21]

3.2 Health

Another outcome variable is health, specifically focusing on diarrheal child mortality, owing to its close relationship with poor sanitation. I use diarrheal mortality rate estimates

[17] Details about the data are provided in Appendix B.

[18] While fecal coliform can also originate from animal waste, the significant effects on fecal coliform observed only after the SBM started, as shown in Panels A and B of Figure 5, suggest that these effects are primarily driven by human waste.

[19] The average values of fecal coliform are used because the actual yearly mean values are only recorded up to 2014. The correlation between average and mean values of fecal coliform is 0.997, which suggests that average values are good proxies for mean values.

[20] There are only 28 observations with an average fecal coliform value of 0 out of approximately 7,200 observations in my sample, which are excluded when transforming the fecal coliform values into logarithms.

[21] The 99th, 95th, 90th, and 75th percentiles of fecal coliform values in the final sample of the water quality analysis are 0.674, 0.056, 0.018, and 0.003 million MPN/100 mL, respectively.

(per 1,000 children) from 2000 to 2019, provided as 5 km raster data by the Institute for Health Metrics and Evaluation (IHME, 2020a). This dataset includes estimates of diarrheal mortality rate in five age groups: early-neonatal (0–6 days), late-neonatal (7–27 days), post-neonatal (28 days–1 year), ages 1–4 years, and under 5 years. These estimates are constructed based on geocoded datasets from multiple household surveys, including the India National Family Health Survey, the India District Level Household Survey, and the India Human Development Survey.[22] For the analysis, the district-level mean of these estimates is computed based on raster data and district boundary data.

3.3 Latrines

The treatment variable is the number of household latrines. I use administrative data on the district-level number of household latrines in rural India from 2012 to 2019, scraped from the database that records toilet construction under the SBM policy. Based on this dataset, the number of latrines per square kilometer is computed as a normalized measure.[23]

One concern with this dataset is that the number of latrines may have been overreported because the data were collected by the Indian government under the SBM policy with the aim of achieving universal latrine coverage. Such overreporting could lead to a downward bias in the magnitude of the estimates because the actual number of latrines may be lower than those reported in the administrative data. In other words, the reported effects on water quality and health in this paper represent lower-bound estimates and could be even larger in reality. As a partial solution to this concern, district (or monitoring station) and year fixed effects in the empirical analyses control for level differences across districts and nationwide trends in overreporting. Moreover, the heterogeneity in effects by fecal sludge treatment capacity remains unaffected if overreporting impacts both high- and low-capacity areas similarly and is differenced out.

3.4 Available Water Capacity

For the IV design, I use AWC as an instrument for latrine construction. AWC is the amount of water that a soil can store that is available for use by plants. AWC represents the soil

[22] IHME (2020a) applies a Bayesian model-based geostatistical framework to 15 geocoded variables and 3 national-level time-varying variables to predict the posterior distributions of diarrheal mortality. One of the national-level time-varying variables is the percentage of the population with access to improved latrines, but my analysis controls for these by including year fixed effects.

[23] My analysis does not consider whether constructed latrines are used owing to a lack of district-level panel data on latrine usage. Because non-use of constructed latrines has been documented in India (Coffey et al., 2014), my estimates represent a lower bound and could be even larger if the number of used latrines (or households using latrines) were used as the treatment indicator instead.

infiltration rate, that is, the velocity or speed at which water enters the soil. Higher AWC is associated with a lower soil infiltration rate. The AWC data are available in the Harmonized World Soil Database v1.2, provided by the Food and Agriculture Organization of the United Nations. This database provides 30 arc-second raster data for AWC across the globe. I compute the district-level mean AWC for the analysis based on the raster data and district boundary data because AWC is mostly distributed contiguously within districts, as shown in Appendix Figure E2.

3.5 Other District Characteristics

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

3.6 Data Matching and Sample Construction

To match the water quality data with other data, I first use the 2011 district boundary data of the ML Infomap and the GPS coordinates of the monitoring stations to identify the district where each monitoring station is located. This process results in the unique assignment of each station to a specific district. I then match the water quality data with the latrine data based on the district names.[24] All other data are similarly matched to the water quality and latrine data following the 2011 district boundary.

After data matching, I construct an unbalanced panel data of 1,189 water quality monitoring stations in 337 districts between 2012 and 2019 for the baseline water quality analysis.[25] For the health analysis, I construct a balanced panel of the same 337 districts from 2012 to 2019. In the reduced-form event study analysis in Section 4.3, I use a longer panel of water quality and health data from 2007 to 2019. In the upstream–downstream specification, I focus on a subset of monitoring stations and districts along major rivers, resulting in a sample of 365 stations in 154 districts for the water quality analysis and a sample of 103 districts for the health analysis, as explained in Section 4.2.

[24] 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.

[25] My analysis focuses only on districts that have monitoring stations. The average number of stations per district is 3.5, with a standard deviation of 3.4.

Table 1 presents summary statistics for the variables used in the main analysis.[26] To evaluate the representativeness of my samples relative to all districts in India (640 districts in 2011), I conduct balance tests by comparing pre-SBM means of key variables. Appendix Table F2 shows that the treatment-related variable, latrine coverage, is almost balanced between my sample districts and the remaining districts (Columns 5-7). Moreover, the health outcome, diarrheal mortality rate, is balanced between the upstream–downstream sample districts, which are used for health analysis, and the remaining districts (Column 7).[27] Balance tests on other variables show that my samples are more populated and less developed (or more rural), where the SBM is likely to be intensively targeted and implemented.

4 Empirical Strategy

I empirically examine the effects of latrine construction under the SBM on river water quality and health. Ordinary least squares (OLS) estimates may be biased due to reverse causality and time-varying omitted variables affecting both latrine construction and outcomes. For example, an increase in diarrheal mortality rate may encourage latrine construction to address this health issue, leading to reverse causality. Moreover, unobserved practices of open defecation may discourage latrine construction while also increasing water pollution.

To identify the causal effects of latrine construction, I adopt an IV design that exploits the geographical variation in soil characteristics that affect the feasibility of latrine construction.

4.1 Instrumental Variable Design

In the IV design, I use AWC, a proxy for soil infiltration rate, interacted with a post-SBM indicator as an instrument for latrine construction to examine the effects of latrine construction on water quality and health.

Higher soil infiltration rates (lower AWC) increase the risk of groundwater contamination from fecal sludge accumulated in pit latrines, which are widely adopted in rural India. Pit latrines consist of a hole called a pit that accumulates fecal sludge without a completely sealed wall. Therefore, pathogens inside fecal sludge can percolate into soils, potentially causing fecal contamination of groundwater sources such as tube and dug wells.[28] The degree of fecal contamination depends on the soil infiltration rate.

[26] Appendix Table F1 shows the summary statistics of variables used for robustness checks.

[27] A balance test on water quality outcomes is not conducted because the remaining districts outside my sample districts, by design, do not have water quality monitoring stations along rivers.

[28] This groundwater contamination is different from river pollution caused by the dumping of fecal sludge emptied from latrines. The former (related to AWC) is considered to motivate the IV design, while the latter (related to STPs) is the effect investigated in this paper.

To address the risk of groundwater contamination, an official technical guideline (CPHEEO, 2013), which has been effective since the SBM's inception in 2014, requires additional precautionary measures for latrine construction in areas with high infiltration rates (lower AWC). Specifically, if the effective size (ES) of the soil is 0.2 mm or less, that is, a lower infiltration rate (higher AWC), pits can be located at a minimum distance of 3 m from water sources.[29] However, for coarser soils with an ES greater than 0.2 mm, that is, a higher infiltration rate (lower AWC), the 3 m minimum distance is insufficient, requiring a greater separation with increased minimum distances. Alternatively, households can maintain the same 3 m minimum distance by making additional investments in latrine construction. Specifically, the bottom of the pits must be sealed with impervious materials such as puddle clay and plastic sheeting, and a 500 mm thick envelope of fine sand of 0.2 mm ES must surround the pit.[30] In short, higher infiltration rates (lower AWC) make it more difficult to find space for latrines and increase construction costs because of the need for additional investments after the SBM started in 2014.[31] These additional requirements are expected to be particularly substantial in rural India, where houses are typically closely spaced, and financially constrained households are unlikely to afford additional investments beyond the fixed subsidy amount, which does not depend on AWC levels.

Therefore, in the first stage of the IV design, areas with a lower AWC are expected to experience a smaller increase in the number of latrines post-SBM. As expected, I find that a 1 mm/m decrease in AWC is associated with a smaller increase in the number of latrines per square kilometer by approximately 0.3 (Column 2 of Tables 2 and 3). The F-statistics of the first-stage regressions are 30–50 for the water quality analysis and 79 for the health analysis. Relatedly, Figure 3 shows the substantial variation in AWC across districts in India.

In the water quality analysis, I adopt the following two-stage least squares regressions, where regressions 1 and 2 are the second- and first-stage regressions, respectively. This IV design is conceptually similar to the DiD design, in which the reduced-form regression in this IV design uses AWC as a treatment variable.

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

[29] This requirement applies to dry pits under unsaturated soil conditions, that is, where the height between the bottom of the pit and the maximum ground water level throughout the year is 2 m or more. In the other case of wet pits under saturated soil conditions, the minimum distance is increased to 10 m.

[30] Noncompliance with the requirements in the technical guideline can weaken the first-stage relationship. However, I find that the F-statistics of the first-stage regressions are not too low and show the confidence interval of the Anderson and Rubin (1949) test, which is robust to the weak instrument in Section 5.

[31] This consideration of AWC applies not only to pit latrines but also to latrines with septic tanks, which are usually equipped with soak pits that treat septic tank effluent. Soak pits are subject to similar requirements that depend on soil infiltration rates to prevent groundwater contamination (CPHEEO, 2013).

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

where $Y_{i,d,t}$ is a water quality indicator, represented by the logarithm of fecal coliform, at monitoring station i located in district d in year t. $Latrine_{d,t}$ is the number of household latrines per square kilometer in district d in year t. $Precip_{d,t}$ is the precipitation in district d in year t, which is added to control for rainfall and associated floods, which may affect both water quality and latrine construction. I construct a time-variant instrument for the panel data analysis by interacting the time-invariant AWC in district d with a post-SBM indicator that takes the value of one after 2014, when the SBM started. Monitoring station fixed effects (δ_i) are included to control for the time-invariant characteristics of each monitoring station (and, more broadly, of each district), including the positions of stations along rivers and cross-sectional socioeconomic disparities across districts. Year fixed effects (θ_t) are also included to account for secular trends in water quality over time, which may be influenced by changes in water quality regulations. Standard errors are clustered at the district level because variation in the number of latrines is observed at this level.

The coefficient of interest is β_{IV} and is expected to be positive in the water quality analysis. My IV estimates, both in the baseline and upstream–downstream specifications, capture the local average treatment effect (LATE) of latrine construction. This LATE is likely to be primarily driven by backward districts, where latrine construction is more constrained by higher costs or difficulties when AWC is lower. As these districts are likely the main beneficiaries of the SBM subsidy program, the IV estimates are well-suited to represent the effect of latrine construction under the SBM policy. I discuss how the characteristics of these complier districts may affect the differences between the OLS and IV estimates in Section 5.

The IV design builds on the key assumption of exclusion restrictions: the instrument ($AWC_d \cdot Post_t$) must affect outcomes only through the channel of latrine construction after controlling for precipitation, monitoring station fixed effects, and year fixed effects. Conditioning on monitoring station fixed effects implies that any violation of the exclusion restriction would arise from time-varying monitoring station (or district) characteristics that are correlated with AWC and change post-SBM.

To address the concern of exclusion restrictions, I choose fecal coliform as a water quality outcome. One potential concern is that AWC, which measures soil quality, affects the agricultural yield of crops. This, in turn, can affect the volume of agricultural runoff, leading to changes in water quality. Therefore, as a water quality outcome, I use fecal coliform, which is primarily affected by fecal sludge from latrines and is unrelated to crop production.

In the health analysis, the exclusion restriction is a more legitimate concern, which motivates me to adopt the upstream–downstream specification described in the following section. For instance, AWC might affect the agricultural yield of crops, which, in turn, could determine household income. This change in income could affect the level of health investment, leading to changes in health conditions.[32] To address this concern, I adopt the upstream–downstream specification, using upstream AWC as an instrument for upstream latrine construction, and examine its effect on downstream outcomes. Further tests to check the validity of the exclusion restriction, including parallel pre-trends and falsification tests, are presented in Section 4.3.

4.2 Upstream–Downstream Specification

The negative externalities of water and health may spill over to downstream areas because dumped fecal sludge can flow downstream along rivers. Thus, I adopt an additional upstream–downstream specification to examine the effects of upstream latrine construction on downstream water quality and health.

The upstream–downstream specification addresses the concern of exclusion restrictions in the baseline IV specification. The baseline specification is modified using upstream AWC as an instrument for upstream latrine construction to examine its effects on downstream outcomes while controlling for downstream AWC. Upstream AWC may affect upstream agricultural output and income, which, in turn, could affect health outcomes in the same area. However, I do not expect upstream AWC to affect downstream health outcomes through changes in downstream income, as upstream AWC is unlikely to affect downstream agricultural output after controlling for downstream AWC. Therefore, by adopting upstream AWC, which is unrelated to downstream agricultural output and income, as an instrument and focusing on downstream health as an outcome, this specification addresses the concern of the exclusion restriction. In other words, the upstream–downstream specification, which relies on the instrument and outcomes in different locations along the rivers, enhances the validity of the exclusion restriction.[33]

I identify the upstream–downstream relationships between monitoring stations and districts using elevation data along 43 major rivers.[34] The analysis focuses on a subset of monitoring stations and districts located along these major rivers, with districts situated

[32] Although district fixed effects control for time-invariant agricultural productivity across districts, differential growth in agricultural yield and income caused by different levels of AWC may still be present.

[33] This approach of using upstream–downstream relationship in the IV design aligns with the methodology adopted in Dias et al. (2023).

[34] 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 also use 90 m raster elevation data, called the Shuttle Radar Topography Mission data Version 4.1 (Reuter et al., 2007).

further upstream.[35] As shown in Figure 4, the upstream districts of a given district (station) are selected as those that intersect with river segments whose elevations are higher than that of the given district (station).[36]

The definition of upstream districts, that is, how far upstream one should search for districts, matters because 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) to identify the upstream districts. Specifically, for a given district (station), the upstream districts are selected from those that fall within a range of $[X, Y]$ km of the given district (station), where $X \in \{0, 50, 100\}$, $Y \in \{100, 150\}$, and $X < Y$. I use a range of $[0, 150]$ km as the baseline specification; however, the results remain robust when using alternative buffer sizes or when considering all upstream districts without buffers, as shown in Appendix Table F3.

The upstream–downstream analysis adopts regressions 3 and 4 modified from the baseline IV specification. I change the independent variable to the upstream number of latrines per square kilometer, and the instrument to the upstream AWC.[37] 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 the outcomes.

$$Y_{i,d,t} = \delta_i + \theta_t + \beta_{IV}^{U} Upstream\_Latrine_{d,t} + \gamma_1 Precip_{d,t} + \gamma_2 AWC_d \cdot Post_t + \varepsilon_{i,t} \tag{3}$$

$$\begin{aligned} Upstream\_Latrine_{d,t} = \delta_i + \theta_t + \pi_1 Upstream\_AWC_d \cdot Post_t + \pi_2 Precip_{d,t} \\ + \pi_3 AWC_d \cdot Post_t + \nu_{d,t} \end{aligned} \tag{4}$$

In the health analysis, the outcome variable ($Y_{d,t}$) is defined as the district-level diarrheal child mortality rate. I focus specifically on the post-neonatal mortality rate because it is the closest available measure to the infant mortality rate, which is known to be significantly impacted by poor sanitation and water pollution (Do et al., 2018; Geruso and Spears, 2018).[38] As the health analysis uses district-level panel data, district fixed effects are used instead of monitoring station fixed effects. The standard errors are clustered similarly at the district

[35] This focus results in a sample of 365 stations in 154 districts for the water quality analysis and a sample of 103 districts for the health analysis. Here, I also drop districts where more than one major rivers flow owing to the complexity of determining the upstream–downstream relationships.

[36] As this process is repeated for all districts (stations) along major rivers, nearly all districts (except for the most downstream ones) are used as upstream districts in the analysis. Thus, there is limited concern that specific characteristics of upstream districts are driving the upstream–downstream results.

[37] If there are multiple upstream districts, I construct the independent variable by dividing the total number of latrines by the total area of these districts. Additionally, I construct the instrument by taking the average of the AWC values from these districts.

[38] Post-neonatal and infant mortality rates 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.

level.

The coefficient of interest β_{IV}^{U} captures the effect of upstream latrine construction, which comprises two underlying channels: (i) the direct effect of upstream latrine construction on outcomes and (ii) the indirect effect of upstream latrine construction on outcomes via correlated latrine construction in the reference district, as illustrated in Appendix Figure E3. The correlation between latrine construction in upstream and reference districts in the second channel arises because this upstream–downstream specification does not explicitly control for latrine construction in the reference district. The presence of both channels indicates that this analysis captures the combined effects of both the spillover effect (first channel) and the local effect (second channel).[39] Although this analysis does not disentangle the two effects, the total effects of water pollution externalities from latrine construction should remain a key policy interest.

I expect that, in the first channel, upstream latrine construction leads to water pollution that flows downstream, subsequently causing a negative externality to health in the reference district. In the second channel, latrine construction in the reference district, which is positively correlated with upstream latrine construction, is expected to contribute to increased water pollution in the same district.[40] The sign of the health effect in the second channel depends on the relative magnitude of the direct positive health effects and water pollution externalities resulting from latrine construction (reduced open defecation) in the reference district. Thus, β_{IV}^{U} is expected to be positive for the water quality outcome because an increase in water pollution is expected in both channels. However, the sign of the overall health effect is ambiguous because it depends on the sign and relative magnitude of the health effect in each channel. For example, if the net health effect becomes positive in the second channel and the magnitude of this net positive health effect surpasses that of the water pollution externalities in the first channel, the overall estimated health effect could be positive.

4.3 Validity of Exclusion Restriction

Two tests are conducted to check the validity of the exclusion restriction: parallel pre-trends and falsification tests.

[39] One potential approach to isolate the spillover effect from the local effect would be to control for latrine construction in the reference district by using AWC in that district as an additional instrument, resulting in two endogenous variables and two instruments. However, I do not adopt this approach owing to the associated weak instrument issue. For the same reason, this approach was not used as the main specification in the analogous upstream–downstream analysis by Dias et al. (2023).

[40] The positive correlation of latrine construction is expected because upstream and reference districts are usually subject to similar levels of SBM policy implementation by the same state government, which is discussed in Section 5.2.

First, I check parallel pre-trends in the reduced-form regressions of water quality and health outcomes on the interaction of AWC with the year dummies. The exclusion restriction implies that AWC should not affect outcomes through other channels before the implementation of the SBM policy. During the pre-SBM period, AWC is unlikely to affect latrine construction because the official technical guideline, which stipulated requirements based on soil infiltration rates, was not published until 2013, just before the start of the SBM.[41] Thus, the association between AWC and outcomes during the pre-SBM period captures causal pathways other than the latrine construction. Conversely, after the SBM started to incentivize latrine construction in 2014, AWC is expected to have a significant relationship with outcomes by affecting latrine construction. By extending the upstream–downstream specification, I test whether upstream AWC has differential effects on outcomes in the reference district during both the pre-SBM and post-SBM periods. The reference year in this event study analysis is set to 2013, one year before the SBM started.

The reduced-form event study results show that upstream AWC did not have a differential effect on either water quality or health prior to the SBM policy (up to 2013), supporting the validity of the exclusion restriction (Panels B and C of Figure 5). Furthermore, AWC did not have a differential effect on water quality before the SBM policy in the baseline IV specification (Panel A).[42] By contrast, during the post-SBM period, larger AWC values led to an increase in fecal coliform and a decrease in diarrheal post-neonatal mortality rates. The lagged effect on water quality, which became statistically significant several years after the SBM started, aligns with the typical timeline for latrines to fill with fecal sludge and subsequently be emptied, generally taking between 1.5 to 3 years as outlined in the technical guidelines (CPHEEO, 2013). In other words, the onset of the effects corresponds to the timeframe when the disposal of emptied fecal sludge and the resulting water pollution are likely to begin. The gradual increase in net positive health effects can be attributed to the time required for households to change their sanitation behaviors and use the newly constructed latrines more consistently.

While differential pre-trends are not observed in the event study analyses, one may still be concerned that other district-level factors correlated with AWC and changing after 2014, such as post-2014 agricultural policies or weather shocks, could confound the results.[43] These

[41] The non-differential effect of AWC on latrine construction during the pre-SBM period is illustrated in the first-stage event study plots presented in Appendix Figure E4. The differential effect of AWC becomes statistically significant from 2014 onward.

[42] Conversely, a differential effect of AWC on health prior to the SBM policy is observed in the baseline IV specification. Therefore, for the health outcomes, I present only the upstream–downstream results in the subsequent sections.

[43] However, to the best of my knowledge, major agricultural reforms were limited to the 2020 attempt (beyond my sample period) to introduce three new farm acts, following unsuccessful efforts to induce state-

agriculture-related confounders could increase agricultural wastewater (e.g., fertilizer and pesticide pollution) or affect agricultural income, which, in turn, could influence health outcomes. To test for the presence of these confounders indirectly, I examine the effects on a water quality indicator related to agricultural wastewater and a health outcome influenced by income in the following falsification tests.

As a second test of the validity of the exclusion restriction, I conduct falsification tests to examine the effects on water quality and health outcomes that are unrelated to fecal contamination but may be related to my instrument. Specifically, I examine the effects of latrine construction on other water quality indicators from the NWMP dataset, as well as the prevalence of overweight in children aged 0–5 years from IHME (2020b). Reassuringly, I find no effect on nitrate-nitrite levels, which primarily reflect fertilizer contamination in agricultural wastewater, in both the baseline and upstream–downstream specifications (Columns 1–2 of Appendix Table F4). This null result suggests that my health results are not driven by agriculture-related confounders affecting the volume of agricultural wastewater. I also find a largely insignificant effect on water temperature, which is also unrelated to fecal contamination (Columns 3–4).[44] Moreover, I find no effect on overweight prevalence, which could be influenced by agricultural income, in the upstream–downstream specification (Column 9). This null result reinforces my previous argument that, in this specification, my instrument is unlikely to affect health outcomes through the income channel.

5 Results

5.1 Effects on Water Quality

I find that latrine construction under the SBM degrades river water quality, and the water pollution externality spills over to downstream areas.

In the baseline specification, Table 2 shows that one additional latrine per square kilometer increases fecal coliform by 3% on average (Column 3 of Panel A). This IV estimate is substantially larger than the OLS estimate, which is approximately 0.6% (Column 1 of Panel A). This difference may be due to a downward bias in the OLS estimate caused by time-varying omitted variables, such as unobserved practices of open defecation that increase

level agricultural market reforms through two acts in 2017 and 2018 (Chand, 2020).

[44] In further analyses, I find insignificant effects on biochemical oxygen demand (BOD) and dissolved oxygen (DO), both of which measure water contamination from various pollution sources, including agricultural and industrial wastewater (Columns 5–8 of Appendix Table F4). While BOD and DO can also be affected by fecal sludge from latrines, its partial contribution to overall BOD and DO levels may explain the null effects. These results, along with the null effect on nitrate-nitrite, also suggest no major sources of water pollution other than fecal contamination from latrine construction.

water pollution and slow down latrine construction. Another possible explanation is that the IV estimate reflects the LATE in backward districts (as discussed in Section 4.1), where fecal dumping may be more prevalent due to lower awareness of water pollution risks. Moreover, the standard errors remain stable even when adjusted for spatial dependence with a cutoff of 150 km, following the Conley (1999) approach (Columns 1 and 3 of Panel A). The water pollution effect remains robust when the maximum value of fecal coliform is used as an outcome (Appendix Table F5) and when fecal coliform outliers above the 99th, 95th, 90th, and 75th percentiles are removed (Appendix Table F6).

The result of the first stage shows an expected positive association between AWC and the number of latrines (Column 2 of Panel A of Table 2). Although the F-statistics of the first stage are not low (29.954), I compute the 95% confidence interval of the Anderson and Rubin (1949) test, which is robust to weak instruments. The positive left and right ends of the 95% confidence interval ([0.015, 0.049]) show that the results are robust to the Anderson and Rubin (1949) specification.[45]

The total effect of the SBM (hereinafter called "average policy effect") is a 72% increase in fecal coliform, which shows a substantial water pollution externality (Column 3 of Panel A). The average policy effect is calculated by multiplying the estimated coefficient by the difference in the mean number of latrines per square kilometer between the pre-SBM period (2012–2013) and the post-SBM period (2014–2019).[46] Considering the pre-SBM average fecal coliform level of 2.6 million MPN (most probable number) per 100 ml, which already exceeds the permissible maximum levels in "Primary Water Quality Criteria for Bathing Water" (2,500 MPN/100ml), a 72% increase in fecal coliform is economically significant.

My estimate of a 72% increase in fecal contamination owing to the SBM surpasses those of most previous studies. This substantial increase in water pollution can be attributed to more than a doubling of latrine coverage (from 39.2% in 2013) during the SBM period. My estimate is considerably larger than the effect of each additional border crossing induced by a border change on water pollution levels (3% increase) in Brazil (Lipscomb and Mobarak, 2016) and the effect of each additional Clean Water Act grant to wastewater treatment plants on fecal coliform (3.6 % decrease) in the United States (Keiser and Shapiro, 2019).

In the upstream–downstream specification, I find that the water pollution externality of latrine construction spills over to the downstream districts, especially several years after the SBM started. Column 3 of Panel B of Table 2 shows that one additional upstream latrine construction per square kilometer increases fecal coliform by 1.5% on average, which amounts to a total increase of 43% under the SBM. Although this average effect is imprecise, the results

[45] The Anderson and Rubin (1949) confidence intervals are also shown in subsequent tables.

[46] Average policy effects are calculated similarly and presented in subsequent tables.

of the reduced-form event study indicate statistically significant water pollution externalities around the years 2017–2019 (Panel B of Figure 5).[47] Moreover, in the heterogeneous analysis in Section 6.1, I find statistically significant pollution spillover effects when upstream areas have low treatment capacities for fecal sludge (Columns 3 and 5 of Panel B of Table 4). The average effect shown in Column 3 of Panel B of Table 2 obscures these dynamic and heterogeneous effects, leading to the imprecise estimate.

5.2 Effects on Health

I find that latrine construction under the SBM improves overall health, which suggests that the direct positive health effect of reduced open defecation outweighs the negative externality on health owing to increased water pollution.

In the upstream–downstream specification, I find that upstream latrine construction reduced diarrheal post-neonatal mortality in the reference district overall (Column 3 of Panel A of Table 3). Although upstream latrine construction can negatively affect health by causing water pollution spillovers to the reference district (the direct effect discussed in Section 4.2), it can also improve health outcomes via correlated latrine construction (reduced open defecation) in the reference district (the indirect effect discussed in Section 4.2). The overall positive health effect indicates that the net positive health effect from increased latrine construction in the reference district outweighs the water pollution externalities from the upstream districts. This overall positive health effect remains robust when the diarrheal mortality rates for other age groups are used as outcomes (Appendix Table F7).

As supporting evidence for the indirect effect, I find a positive correlation between latrine construction in the upstream and reference districts (Column 3 of Panel B of Table 3). This positive correlation can be attributed to the fact that these districts are usually located within the same state, given that the buffer size for identifying the upstream districts is 150 km.[48] Because states play a central role in implementing the SBM policy in India, districts within the same state are likely to undertake similar levels of latrine construction.[49] While other state-level policies, such as agricultural policies, could similarly lead to correlated agricultural investments across districts and affect health outcomes through changes in agricultural wastewater or income, the pre-trends and falsification tests in Section 4.3 suggest a low likelihood of these alternative channels.

[47] This lagged effect on water quality starting from 2017 can be explained by the pit filling and emptying frequency, as discussed in Section 4.3.

[48] 84% of the 103 reference districts have at least one upstream district within the same state.

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

Regarding the magnitude of the health effect, one additional upstream latrine construction per square kilometer reduces the diarrheal post-neonatal mortality rate per 1,000 children by 0.011, which is a 0.4% decrease from the pre-SBM period (Column 3 of Panel A of Table 3).[50] The average policy effect of the SBM is calculated to be a 0.269 reduction in diarrheal post-neonatal mortality rate per 1,000 children, which amounts to a 10% reduction from the pre-SBM period. This total 10% reduction in diarrheal mortality under the SBM policy is smaller than the effects noted in previous studies, such as that of Geruso and Spears (2018), who reported a 48% decrease in the infant mortality rate associated with a 60 percentage point reduction in the fraction of neighbors defecating in the open, a change similar in magnitude to the SBM policy. This discrepancy suggests the presence of water pollution externalities, which I additionally consider in this paper.

5.3 Robustness Checks

The results are robust to an alternative DiD design, consideration of spillovers from neighboring districts and urban areas, and the adoption of a balanced panel and alternative mortality dataset.[51]

Alternative DiD Design.—I adopt a DiD design that exploits the differential increase in latrine coverage across districts with different levels of baseline coverage. All districts achieved almost universal latrine coverage by the target date of 2019, regardless of their baseline latrine coverage. Consequently, districts with lower baseline latrine coverage experienced a larger increase in latrine coverage, which may have led to a larger increase in water pollution. The DiD design thus uses the baseline latrine non-coverage in 2013, interacted with a post-SBM indicator, as a treatment variable (see Appendix C for more details).

As shown in Appendix Table C1, the DiD results are similar to those of the IV design. I find a negative effect on water quality, although the overall effect is imprecise (Column 1). Consistent with the heterogeneous effects shown in Section 6, this negative effect is significant only in areas with lower treatment capacities (Columns 2–5). The event study results show that parallel pre-trends hold, and the water pollution effect becomes more pronounced over time in states with lower treatment capacities (Panel B of Appendix Figure C3).

Spillovers from Neighboring Districts.—The baseline analysis assumes that the water quality

[50] The IV estimate is larger in magnitude than the OLS estimate (Columns 1 and 3 of Panel A of Table 3). This difference may be due to bias in the OLS estimate caused by reverse causality, where an increase in the diarrheal mortality rate leads to more latrine construction as a response. Another possible explanation is that the LATE in the IV design is driven by backward districts (as discussed in Section 4.1), which have greater potential for reducing diarrheal mortality due to their higher baseline levels.

[51] While I mainly test the robustness of the baseline results, I also discuss the robustness of the results of heterogeneous effects that are examined in Section 6.

at a given monitoring station is affected only by latrine construction in the district where the station is located. However, monitoring stations can be situated in rivers flowing along the borders of several districts. In this case, the water quality at these stations is likely to be affected by these neighboring districts. Therefore, I conduct an additional analysis that incorporates spillover effects from neighboring districts. For monitoring stations located within 2 km of more than one district, I compute the weighted average of variables of neighboring districts using district areas as weights. Data from other monitoring stations remain unchanged. I then re-run the baseline IV regression using this modified dataset.

As shown in Appendix Table F8, I find similar results: a negative effect on water quality (Column 1), driven by areas with lower treatment capacities (Columns 3 and 5).

Influence from Urban Areas.—While this paper focuses on the effects of latrine construction in rural India, the results could also be driven by latrine construction in urban areas. Therefore, I estimate the effects after excluding monitoring stations and districts close to urban areas from the sample. Specifically, I drop monitoring stations and districts within 50, 100, or 150 km of cities with a population of 1 million or more, according to the 2011 Census.

As shown in Appendix Table F9, the results are robust to the exclusion of urban areas, regardless of distance. I find a negative effect on water quality, while the health effects remain positive but become less precise, possibly due to stronger offsetting by water pollution effects.

Balanced Panel.—The baseline analysis uses an unbalanced panel of water quality data to cover as many districts as possible to enhance the external validity of the results. As a robustness check, I conduct the same analysis on a balanced panel to mitigate the concern that monitoring stations may have been endogenously installed in less-polluted locations over the sample period. As shown in Appendix Table F10, I find a negative effect on water quality, especially in areas with lower treatment capacities.

Alternative Mortality Dataset.—The baseline health analysis uses diarrheal mortality rate estimates from IHME (2020a) as outcomes, but these are predicted based on multiple household surveys. Thus, I conduct the robustness check using the original infant mortality data from the National Family Health Survey 5 (NFHS-5), conducted in 2019–2021. From the birth histories of women in households surveyed in NFHS-5, I use data concerning the year of childbirth and whether the child died within 12 months of birth, which serves as an infant mortality indicator.[52] I then conduct the same upstream–downstream analysis on this alter-

[52] The NFHS data is limited by its mortality indicator encompassing all types of mortality rather than isolating those caused by water pollution, such as diarrheal mortality, which is why I do not adopt this dataset in the baseline specification. To match the NFHS-5 dataset with other datasets, I use the year of birth of the child and the geocoordinates of NFHS clusters (villages).

native outcome by focusing on children living close to rivers (within 5 or 10 km).[53] These children are more likely to be exposed to water pollution externalities from latrine construction that flow along rivers, as examined in the upstream–downstream analysis. Although the outcome in this analysis is measured at the child level, the district-level variables remain the same as in the baseline health analysis, with additional controls included at the child and household levels.[54]

As shown in Column 1 of Appendix Table F11, I find a consistent overall positive health effect, regardless of distance. The magnitude of this effect is a reduction in the infant mortality rate by 1.3–2.0 per 1,000 children, representing a 3.4–5.5% decrease from the pre-SBM period.[55] This effect size is larger than the baseline result for the diarrheal post-neonatal mortality rate, likely due to the inclusion of a broader age range (including neonatal) and the influence of other mortality causes correlated with diarrheal mortality. Regarding the heterogeneous effects of the treatment capacity of fecal sludge, the positive health effects are smaller or statistically insignificant when upstream areas have lower treatment capacities (Columns 2-5), as demonstrated in the heterogeneity analysis in Section 6.2.

6 Heterogeneous Effects by Treatment Capacity of Fecal Sludge

To identify the mechanism behind the negative externalities on water quality and health, I examine whether the effects of latrine construction on water quality and health vary by the level of complementary infrastructure for the treatment of fecal sludge. The negative externalities are pronounced in areas with lower treatment capacities, where dumping of untreated fecal sludge is more likely to occur. This suggests that insufficient treatment (or dumping) of fecal sludge is the primary mechanism driving these negative externalities.

In the heterogeneity analysis, 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 the state and district levels in 2013, one year before the SBM started.[56] The baseline level of STP capacity is adopted to address concerns about the en-

[53] I use rivers $\geq$30 m wide at mean annual discharge, available in the Global River Widths from Landsat Database (Allen and Pavelsky, 2018). This dataset covers smaller rivers than the dataset of major rivers used to identify upstream districts. Including smaller rivers enables me to capture the pollution exposure of children living near these rivers, which branch out from the major rivers and are affected by their pollution.

[54] Child-level controls include indicators for being a first-born child and part of a multiple birth. Household-level controls include religion (Hindu, Muslim, others), caste (Scheduled Caste, Scheduled Tribe, Other Backward Class, others), education (primary, secondary, or higher), and wealth quintiles.

[55] Average policy effects are not presented in this robustness check because using the change in the number of latrines for the entire district to scale the effect only on children near rivers may not provide accurate estimates of the average policy effects. The same applies to the analysis of diarrheal mortality rates in river-adjacent areas, as discussed later in Section 6.2.

[56] The district-level STP capacities are susceptible to measurement errors owing to missing observations

dogenous construction of STPs in response to water pollution caused by latrine construction. While a potential concern of using the baseline STP capacity is that treatment effects could also be mediated by STP construction during the post-SBM period, CPCB data shows that the change in STP capacity during this period was limited.[57] Therefore, in the baseline specification, I compare the effects in states (districts) that have higher baseline treatment capacities than the median in the sample with those in states (districts) with lower treatment capacities.[58] In the upstream–downstream specification, I examine the heterogeneous effects of different levels of baseline treatment capacities in upstream states (districts).

This heterogeneity analysis does not explicitly consider STP treatment fees, which can also affect the amount of treated fecal sludge due to data limitations. However, this approach is justified because the tipping fees for discharging at STPs are substantially lower than the revenues generated from emptying latrine pits for desluding truck operators.[59] This context suggests that truck operators are likely to transport fecal sludge to STPs when available. Furthermore, variations in STP capacity implicitly account for variations in fees, as larger capacities are expected to result in lower marginal treatment costs and tipping fees.

6.1 Effects on Water Quality

I find that the negative externality of water quality is concentrated in areas without adequate wastewater infrastructure. As shown in Table 4, an additional latrine per square kilometer leads to a 5.1% (3.7%) increase in fecal coliform in districts (states) with lower treatment capacities, which amounts to a 134% (98%) increase under the SBM (Columns 3 and 5 of Panel A). Conversely, I find insignificant effects in states and districts with higher treatment capacities (Columns 2 and 4 of Panel A). Similarly, in the upstream–downstream

of STPs in the CPCB inventory. Some districts may be flagged as districts with zero treatment capacity owing to missing observations, even though they may actually have STPs. Therefore, I also use state-level STP capacities, which are less susceptible to measurement errors because of broader aggregation.

[57] First, consistent with the fact that planning and constructing STPs can take 5–10 years, the total STP capacity across India increased by only 52% from 2013 to 2021, even though latrine coverage more than doubled in the same timeframe. Second, areas with lower baseline STP capacities did not experience a more substantial increase in STP construction, as indicated by the positive correlation between the baseline level of STP capacity in 2013 and the change in STP capacity from 2013 to 2021 at the state level (analysis based on CPCB (2015, 2021)). This second finding shows that baseline STP differences do not disappear or reverse during the post-SBM period.

[58] I present heterogeneity results based on subgroup analyses rather than analyses using interaction terms between latrine construction and the high-capacity indicator because the latter approach introduces two endogenous variables and two instruments, leading to a weak instrument issue. The median value is calculated after assigning zero capacity to the states (districts) without any STP.

[59] The tipping fees for discharge at STPs are approximately USD 1.2 (INR 100) and USD 6 (INR 500) per visit per truck in Chennai and Goa, respectively, according to case studies in Gupta et al. (2018). These fees are much lower than the revenues of truck operators, who typically charge between USD 6-30 (INR 500-2500) per household and visit a large number of households before discharging at STPs (Rao et al., 2020).

specification, I find that a negative externality from upstream latrine construction spills over downstream only when upstream areas have lower treatment capacities. The magnitude of these effects (82-114% increase under the SBM) is comparable to those observed in the baseline IV specification (Columns 3 and 5 of Panel B).[60]

These differential effects by the treatment capacity of fecal sludge suggest that the dumping of fecal sludge emptied from latrines is the primary mechanism contributing to increased river pollution. In contrast, the insignificant effect on water quality in areas with higher treatment capacities suggests a low probability that alternative mechanisms, such as the direct seepage of fecal matter from latrines into rivers, affect water quality.

6.2 Effects on Health

I find that the overall positive health effect is eliminated when upstream areas lack adequate wastewater infrastructure. The heterogeneity analysis allows me to explicitly investigate the negative externality on health through exposure to increased water pollution. A negative externality can be captured as the difference between health effects in areas with lower treatment capacities (where significant river pollution is observed) and those in areas with higher treatment capacities (where river pollution is insignificant).

Table 5 shows the heterogeneous effects on diarrheal child mortality rates by treatment capacities. I find that the total effect of the SBM is a 15% (42%) decrease in diarrheal post-neonatal mortality rate from the pre-SBM period when upstream districts (states) have higher treatment capacities (Columns 2 and 4 of Panel A). This corresponds to the cases in which the water pollution externalities are found to be insignificant in the water quality analysis. However, the positive health effect is eliminated when upstream areas have lower treatment capacities and water pollution externalities are significant (Columns 3 and 5 of Panel A). These heterogeneous health effects remain robust when examining the effects on mean diarrheal mortality rates only in areas close to rivers (within 5 or 10 km), where children are more likely to be exposed to water pollution, as demonstrated in the analysis of the alternative mortality dataset in Section 5.3 (Appendix Table F12).[61]

These findings, together with the water quality results, suggest that increased river pollution owing to the dumping of fecal sludge offsets the direct positive health effects.[62] Although

[60] These insignificant effects in the case of higher treatment capacities also suggest that STP treatment fees do not substantially affect the amount of treated fecal sludge.

[61] A substantial portion of the population in the sample districts used for the health analysis lived in close proximity to rivers. Specifically, 36% of the population resided within 5 km of rivers, while 58% lived within 10 km in 2011, according to the WorldPop 100m raster data. Additionally, for this robustness check, I use the same river dataset adopted in the analysis of the alternative mortality dataset.

[62] Although direct contamination of groundwater in wells by latrines could be another mechanism for this negative health effect, it is less likely because I observe a significant first-stage relationship suggesting that

the overall health effect across India is positive, water pollution externalities diminish the effectiveness of latrine construction in improving child health.

7 Conclusion

My analysis documents the unintended negative consequences of latrine construction when scaled up as a nationwide policy. Although open defecation is commonly blamed for water pollution externalities, I show that large-scale household latrine construction can generate even greater negative externalities due to insufficient infrastructure for fecal sludge treatment.

Specifically, I examine the consequences of the world's largest sanitation policy, the SBM in India, which subsidized the construction of over 100 million latrines. I exploit the SBM's requirements for latrine construction to identify its causal effects on water quality and health. According to the official technical guideline, the soil infiltration rate determines the cost and difficulty of latrine construction after the SBM starts. Therefore, the interaction of the soil infiltration rate with a post-SBM indicator is used as an instrument for latrine construction.

I find that the SBM increases fecal contamination of rivers by 72% in rural India, which is a substantial effect. This water pollution externality exists only in areas with lower treatment capacities for fecal sludge where dumping of fecal sludge is more likely to occur. Although the SBM reduces diarrheal mortality in children by 10% overall, this positive health effect is eliminated when upstream areas have lower treatment capacities. These heterogeneous effects suggest that water pollution externalities owing to the dumping of fecal sludge offset the direct positive health effects of reduced open defecation.

Back-of-the-envelope cost–benefit analyses of the SBM confirm the importance of complementing latrine construction with adequate wastewater infrastructure. The mortality benefit alone is not worth the cost of the SBM policy under insufficient fecal sludge treatment.[63] The mortality benefit, that is, reduction in diarrheal post-neonatal mortality because of latrine construction, is calculated to be USD 5.6 million, which is about one-third of the subsidy cost for latrine construction (USD 16.9 million) at the district level.[64] However, complementing latrine construction with adequate treatment of fecal sludge to mitigate neg-

the latrine technical guideline for preventing groundwater pollution is generally effective.

[63] The total benefits would be larger than the estimated mortality benefit if I also included health effects for other age groups and additional benefits such as improved educational outcomes and reduced violence against women. Conversely, the total costs would be higher if I also considered the reduced recreational value of water quality, or they would be lower if some households do not use the full amount of the subsidy.

[64] District-level cost-benefit analyses are conducted because the health effect sizes used are derived from district-level analyses of health and latrine data. The mortality benefit is calculated using the estimated average policy effect and the value of a statistical life in India. Meanwhile, the subsidy cost is calculated by multiplying the amount of the SBM subsidy by the increased number of latrines under the SBM. More detailed steps are described in Appendix D.1.

ative externalities would substantially increase the mortality benefit at a lower cost. The additional mortality benefit of having higher treatment capacity is calculated to be USD 7.4 million, which is larger than the additional cost of constructing and operating more STPs (USD 4.5 million) at the district level.[65]

The results have several policy implications for developing countries that promote sanitation and other developmental policies. The first clear implication is that policymakers should consider the possibility of the negative externalities of sanitation investments on water quality and health. An enabling environment that includes the effective treatment of fecal sludge by infrastructure can make sanitation policies more effective, which should be strengthened in the second phase of the SBM, starting in 2020. The need for better fecal sludge management is also a common issue in other developing countries, including Bangladesh, Nepal, and Pakistan, despite good progress in improving access to toilets (WaterAid, 2019).

Second, my findings broadly highlight the unintended negative environmental consequences that can arise when a program is scaled up to a nationwide policy. This negative externality of a scaled-up policy aligns with a growing body of research that links conditional cash transfers to deforestation (Alix-Garcia et al., 2013) and rural road access to air pollution (Garg et al., 2023). By connecting a large-scale sanitation policy to water pollution, this paper further demonstrates that intensely promoting private goods without complementary infrastructure investments can cause environmental pollution, consequently reducing the effectiveness of these private goods in improving health.

[65] The additional mortality benefit is calculated based on the difference in the estimated average policy effects between districts with higher and lower treatment capacities. The additional cost is calculated by multiplying the unit cost of sewage treatment plants by the difference in STP capacity between districts with higher and lower treatment capacities. More detailed steps are described in Appendix D.2.

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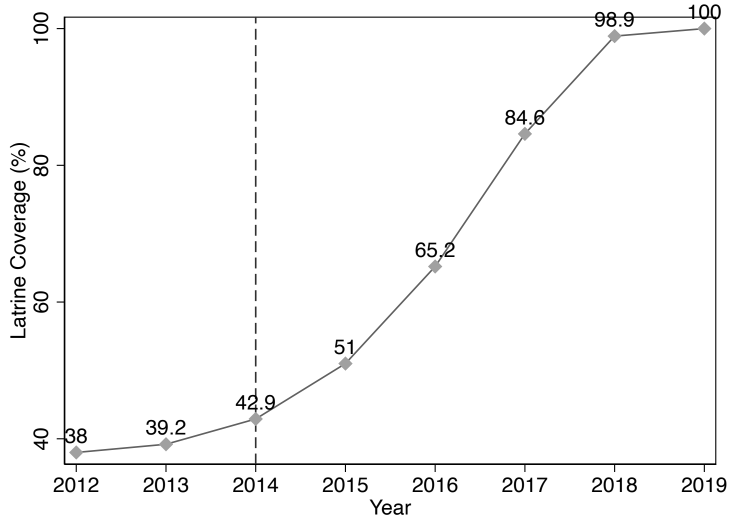

Figure 1: Latrine Coverage in Rural India

Notes: This figure documents the proportion of households that have latrines in rural India between 2012 and 2019, based on the administrative database of the SBM. A vertical dashed line shows the starting year of the SBM.

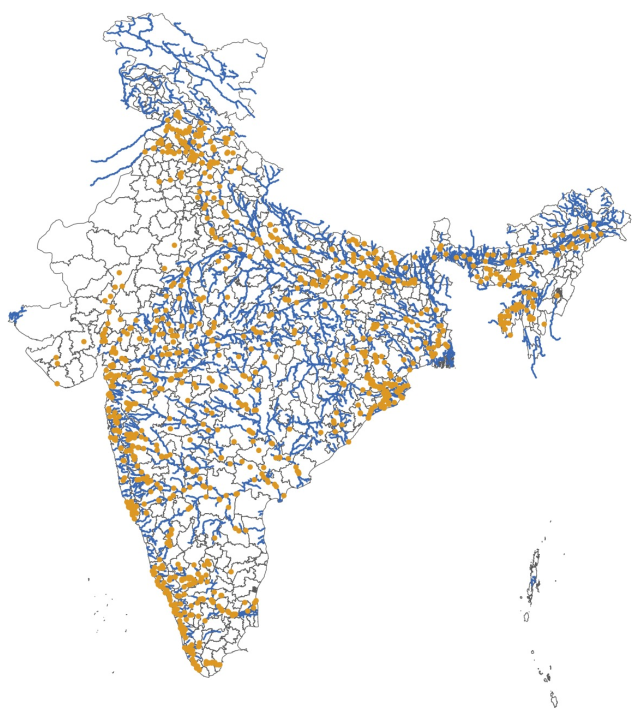

Figure 2: Distribution of Water Quality Monitoring Stations in India

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).

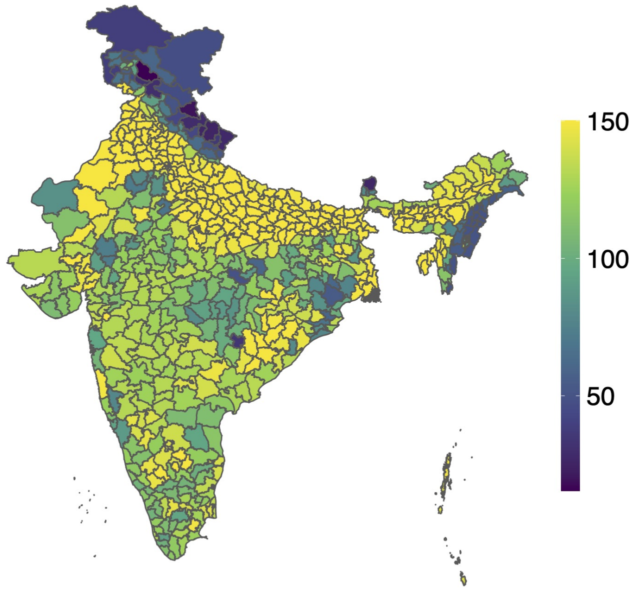

Figure 3: District-level Mean Available Water Capacity (mm/m)

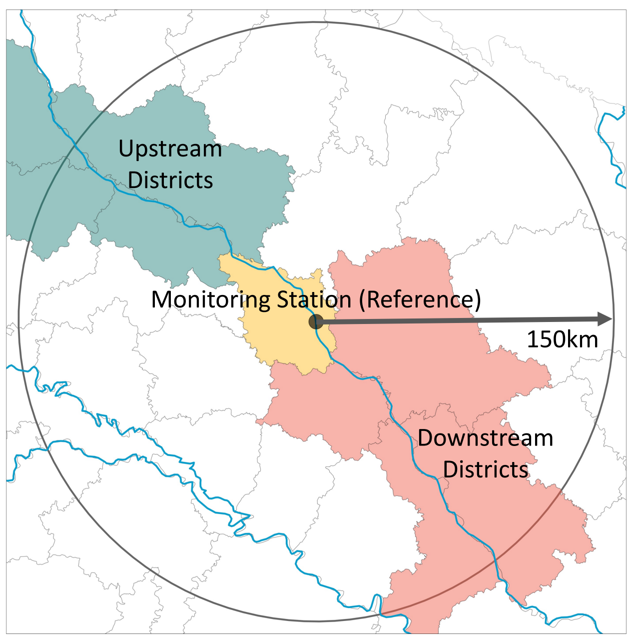

Figure 4: Illustration of Upstream–Downstream Analysis

Notes: This figure illustrates the upstream–downstream analysis, which analyzes the effect of upstream latrine construction on water quality in a reference monitoring station (or health in a reference district). Upstream districts are selected as districts that (i) intersect with river segments whose elevations are higher than the elevation of the reference station (district) and (ii) fall within a range of [0, 150] km from the reference station (district) in the baseline specification. This figure shows district boundaries in grey lines and rivers in blue lines. It highlights the upstream districts in green, the reference district in yellow, and the downstream districts in red.

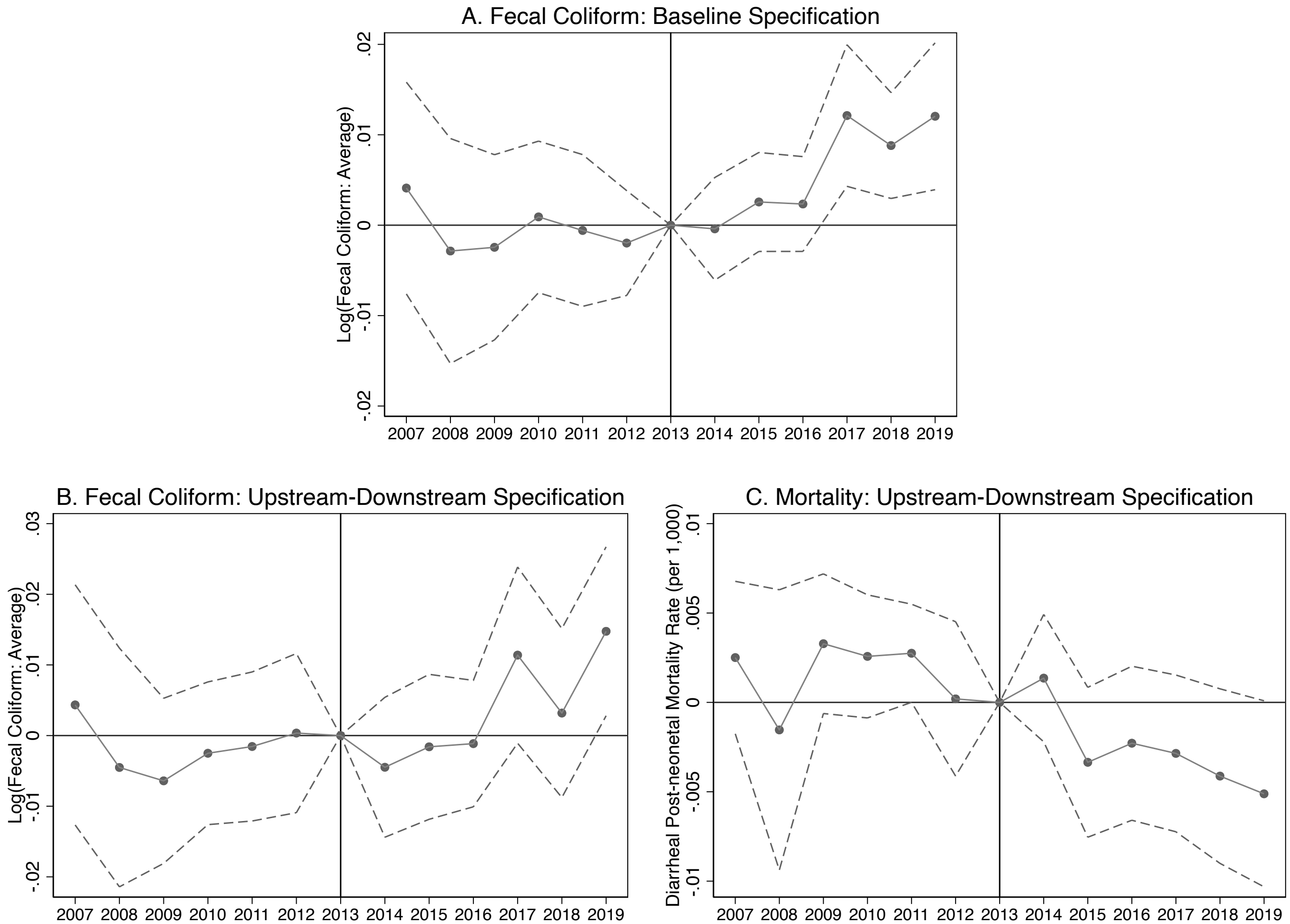

Figure 5: Event Study Plots of Reduced-Form Regressions

Notes: This figure shows the regression coefficients of the logarithm of fecal coliform (Panels A and B) and diarrheal post-neonatal mortality rate per 1,000 children (Panel C) on the interaction terms between Available Water Capacity in Panel A (upstream Available Water Capacity in Panels B and C) 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. Panel B includes monitoring station fixed effects, year fixed effects, and the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district, while Panel C includes district fixed effects, year fixed effects, and the same controls.

Table 1: Summary Statistics

	Mean	SD	Min	Max	Obs.
Panel A. Time-varying variables: pre-SBM (2007-2013)					
Fecal coliform: Average (million MPN/100ml)	2.61	143.77	0	10000.04	4939
Diarrheal post-neonatal mortality rate (per 1,000)	2.69	1.8	0.07	9.48	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
Precipitation (thousand mm)	1.34	0.78	0.21	5.59	1946
Panel B. Time-varying variables: post-SBM (2014-2019)					
Fecal coliform: Average (million MPN/100ml)	0.72	30.39	0	1750.01	5553
Diarrheal post-neonatal mortality rate (per 1,000)	1.46	1.07	0.05	5.21	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
Precipitation (thousand mm)	1.31	0.88	0.2	10.06	1814
Panel C. Variables not varying over time					
Available water capacity (mm/m)	128.03	25.91	19.79	150	337
2013 district-level sewage treatment plant capacity (MLD)	28.17	105.03	0	947.5	337
2013 state-level sewage treatment plant capacity (MLD)	389.93	624.77	0	2307.75	28

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)

	OLS	IV: First Stage	IV: Second Stage
	(1) Log(Fecal Coliform)	(2) # of Latrines per sq. km	(3) Log(Fecal Coliform)
Panel A. Baseline Specification			
Number of latrines per sq. km	0.006***		0.030***
	(0.002)		(0.008)
AWC * Post (=1)		0.283***	
		(0.052)	
Observations	7,201	7,201	7,201
R^2	0.020	0.438	-
Number of Stations	1,189	1,189	1,189
Number of Districts	337	337	337
KP F-Stat	-	29.954	-
AR 95% CI	-	-	[.015, .049]
Conley SE	(0.003)	-	(0.010)
Average Policy Effect	0.142	-	0.719
Panel B. Upstream-Downstream Specification			
Upstream number of latrines per sq. km	0.009***		0.015
	(0.003)		(0.011)
Upstream AWC * Post (=1)		0.322***	
		(0.045)	
Observations	2,228	2,228	2,228
R^2	0.057	0.533	-
Number of Stations	365	365	365
Number of Districts	154	154	154
KP F-Stat	-	50.475	-
AR 95% CI	-	-	[-.008, .039]
Conley SE	(0.003)	-	(0.012)
Average Policy Effect	0.250	-	0.431

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 in Panel A include monitoring station fixed effects, year fixed effects, and precipitation as a control. Regressions in Panel B include monitoring station fixed effects, year fixed effects, and the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district. In Panel B, the sample is limited to monitoring stations located along major rivers in India, and upstream districts are defined as those within the range of $[0, 150]$ km from a reference station. 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 Conley SE refers to the standard errors that are spatially clustered with a cutoff of 150 km following the Conley (1999) approach. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table 3: The Effect on Health (Diarrheal Post-neonatal Mortality Rate)

	OLS	IV: First Stage	IV: Second Stage
	(1) Mortality/Latrine	(2) # of Latrines per sq. km	(3) Mortality/Latrine
Panel A. Dep. Variable: Diarrheal Post-neonatal Mortality Rate (per 1,000) (columns 1, 3)			
Upstream number of latrines per sq. km	-0.005**		-0.011*
	(0.002)		(0.006)
Upstream AWC * Post (=1)		0.301***	
		(0.034)	
Observations	824	824	824
R^2	0.664	0.573	-
Number of Districts	103	103	103
KP F-Stat	-	78.696	-
AR 95% CI	-	-	[-.023, .001]
Mean of Dep. Variable	2.576	23.684	2.576
Average Policy Effect	-0.111	-	-0.269
Panel B. Dep. Variable: # of Latrines per sq. km in a Reference District (columns 1, 3)			
Upstream number of latrines per sq. km	0.894***		0.726***
	(0.109)		(0.154)
Upstream AWC * Post (=1)		0.301***	
		(0.034)	
Observations	824	824	824
R^2	0.796	0.573	-
Number of Districts	103	103	103
KP F-Stat	-	78.696	-
AR 95% CI	-	-	[.404, 1.05]
Mean of Dep. Variable	33.054	23.684	33.054

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 the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district. The sample is limited to districts that have monitoring stations used in the water quality regression along major rivers in India. Upstream districts are defined as those within the range of $[0, 150]$ km from a reference district. 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 means of dependent variables are calculated for the pre-SBM period. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table 4: The Heterogeneous Effects on Water Quality by Treatment Capacity of Fecal Sludge

	All	State-level Capacity		District-level Capacity	
	(1)	(2)	(3)	(4)	(5)
	All	High	Low	High	Low
Panel A. Dependent Variable: Log(Fecal Coliform) - Baseline Specification					
Number of latrines per sq. km	0.030***	-0.031	0.037***	0.014	0.051***
	(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) - Upstream–Downstream Specification					
Upstream number of latrines per sq. km	0.015	-0.046	0.031***	-0.004	0.037*
	(0.011)	(0.032)	(0.011)	(0.011)	(0.023)
Observations	2,228	1,107	1,119	1,097	1,131
Number of Stations	365	171	194	180	185
Number of Districts	154	73	84	75	93
KP F-Stat	50.475	19.767	41.298	53.262	15.137
AR 95% CI	[-.008, .039]	[-.112, .040]	[.010, .063]	[-.033, .018]	[-.013, .121]
Average Policy Effect	0.431	-1.367	0.820	-0.092	1.139

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 in Panel A include monitoring station fixed effects, year fixed effects, and precipitation as a control. Regressions in Panel B include monitoring station fixed effects, year fixed effects, and the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district. In Panel B, the sample is limited to monitoring stations located along major rivers in India, and upstream districts are defined as those within the range of $[0, 150]$ km from a reference station. In Panel A, Column 2 reports a result in states where the treatment capacities of sewage treatment plants are higher than the median, while Column 3 reports a result in states with lower treatment capacities. Panel B instead uses variation in treatment capacities of upstream states in Columns 2 and 3. 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. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table 5: The Heterogeneous Effects on Health by Treatment Capacity of Fecal Sludge

	All	State-level Capacity		District-level Capacity	
	(1)	(2)	(3)	(4)	(5)
	All	High	Low	High	Low
Panel A. Dependent Variable: Diarrheal Post-neonatal Mortality Rate (per 1,000)					
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)
Observations	824	432	392	456	368
Number of Districts	103	54	49	57	46
KP F-Stat	78.696	33.304	33.484	59.873	18.756
AR 95% CI	[-.023, .001]	[-.073, -.024]	[-.026, .002]	[-.030,-.000]	[-.029, .026]
Mean of Dep. Variable	2.576	2.534	2.623	2.428	2.759
Average Policy Effect	-0.269	-1.058	-0.230	-0.364	-0.009
Panel B. Dependent Variable: Number of Latrines per sq. km in a Reference District					
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)

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 the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district. The sample is limited to districts that have monitoring stations used in the water quality regression along major rivers in India. Upstream districts are defined as those within the range of $[0, 150]$ km from a reference district. Column 2 reports results when upstream states have higher treatment capacities of sewage treatment plants than the median, while Column 3 reports results in the case of upstream states with lower treatment capacities. Columns 4 and 5 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 means of dependent variables are calculated for the pre-SBM period. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Online Appendix

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

Kazuki Motohashi

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A Conceptual Framework on Negative Externalities of Sanitation Investment

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

I consider a district with N households that can decide whether to construct a latrine. I assume that a given household can build a latrine by paying a fixed price (p_{pre}).[66] The maximum number of latrines that can be built in a district is $Q^{max} = N$.

The fecal sludge emptied from latrines in this district is treated by STPs. The treatment capacity of the fecal sludge is given by $Q^{stp} \in [0, Q^{max}]$ 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}, $Q - Q^{stp}$ fecal sludge is dumped into rivers, causing negative externalities in 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 ($Q^{stp} > \frac{Q^{max}}{2}$).

Appendix Figure A1 shows the marginal benefit (MB), marginal cost (MC), marginal damage (MD), and social marginal cost (SMC) of latrine construction for the low-treatment (Panel A) and high-treatment (Panel B) capacity cases.

Both panels exhibit the same MB and MC curves. The MB curve represents the direct health benefits from reduced open defecation and exposure to fecal matter near human habitats.[67] This curve is downward-sloping because some households benefit more than others; for instance, if they have more infants who are vulnerable to diarrhea. For MC, the pre-SBM curves are constant at a constant price for latrines ($MC_{pre} = p_{pre}$). The MC curves are shifted downward by the subsidy under the SBM. Households receive a subsidy of approximately USD 140 for latrine construction. Therefore, the post-SBM effective price of latrines ($MC_{post} = p_{post}$) becomes substantially lower than p_{pre}.

The main difference between Panels A and B is SMC. If the treatment capacity (Q^{stp}) is low (Panel A), MD, that is, the negative externality on health through exposure to increased river pollution, becomes nonzero, starting from a lower number of latrines. However, if the

[66] The latrine price can include both the initial construction cost of a latrine and the present value of marginal costs for emptying fecal sludge periodically.

[67] MB is assumed to only represent direct health benefits, that is, reduction in the risks of diarrheal mortality, although there could be other benefits, including an improvement in educational outcomes and reduction in violence against women.

treatment capacity (Q^{stp}) is high (Panel B), then MD occurs only for a large number of latrines. Here, I assume a non-linear dose-response relationship: the larger the volume of dumped fecal sludge ($Q - Q^{stp}$), the larger the marginal negative externality on health (MD).[68] The SMC curves reflect the differences in MD curves, because $SMC = MC + MD$.

Based on this conceptual framework, I examine the welfare effects of latrine construction under the SBM in Appendix Figure A1. 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 the subsidy. Thus, the number of latrines substantially increases from Q^e_{pre} to Q^e_{post}. This increase in latrines causes a large increase in the negative externality owing to the low treatment capacity. The deadweight loss increased substantially from DWL_{pre} to DWL_{post}. Conversely, if the treatment capacity is high (Panel B), the increase in deadweight loss owing to latrine construction is limited because the negative externality only occurs in a large number of latrines. A comparison of Panels A and B suggests that the subsidy under the SBM adversely impacts welfare more substantially in the case of low treatment capacity.

I further examine the effects of latrine construction under the SBM on water quality and health in Appendix Figure A2, which is based on the welfare analysis in Appendix Figure A1. In Appendix Figure A2, the total benefit represents the total direct health effects, whereas the total damage represents the total negative externality on health owing to water pollution.[69] I examine the difference between the total benefit and total damage (net benefit) as a health outcome in the empirical analysis.[70] The total damage can be interpreted as the degree of water pollution, which corresponds to the water quality outcome of the empirical analysis.

This paper estimates the effects of an 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. According to Appendix Figure A2, there are three testable hypotheses for the empirical analyses. The first hypothesis is tested in the baseline analysis (Section 5), and the second and third hypotheses are tested in the heterogeneity analysis (Section 6).

[68] The non-linear relationship is suggested by a classic epidemiological study (Moe et al., 1991), which shows the evidence of threshold effects where significantly higher rates of diarrheal disease are observed once the fecal contamination level in drinking water reaches a certain threshold.

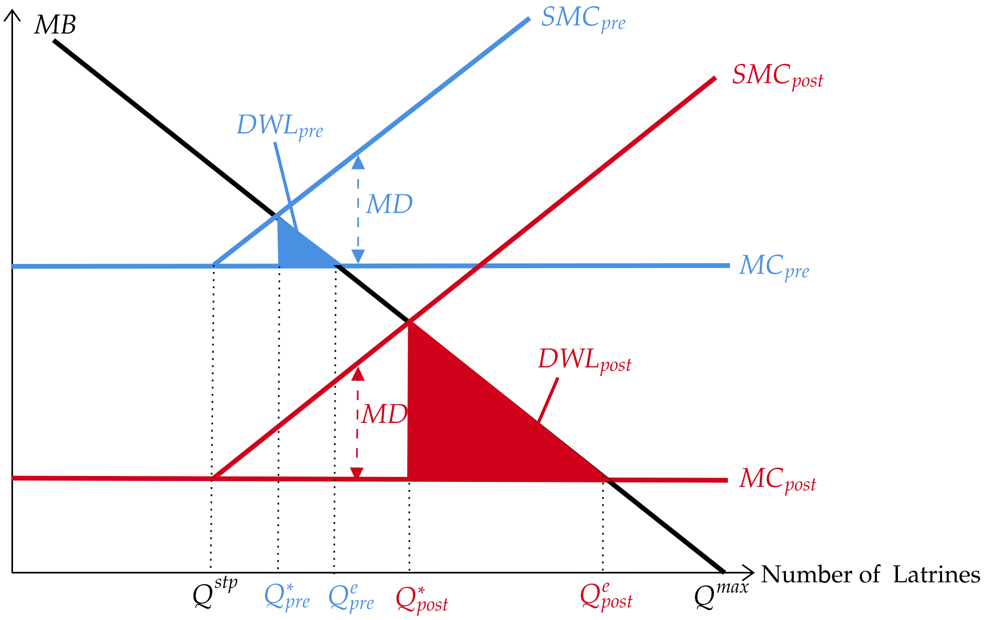
[69] The total benefit in Appendix Figure A2 is the area under the MB curves of Appendix Figure A1. The total damage in Appendix Figure A2 represents the area bounded by the SMC and MC curves shown in Appendix Figure A1.

[70] I assume that the total benefit is larger than the total damage. In this case, the net benefit is positive, which means that latrines are health-improving. This is consistent with the empirical results of this paper.

1. The SBM improves health overall (increase in net benefit) if the total benefit increases more substantially than the total damage and increases water pollution (increase in total damage) regardless of treatment capacity.[71]
2. The magnitude of positive health effects is smaller in the case of low treatment capacity.
3. The magnitude of negative effects on water quality (increased water pollution) is larger in the case of low treatment capacity.

[71] While theoretically, net benefit may decrease, Appendix Figure A2 demonstrates a case where the total benefit increases more substantially than the total damage (increase in net benefit), which is consistent with the empirical results of this paper.

Panel A. Treatment Capacity Low



Panel B. Treatment Capacity High

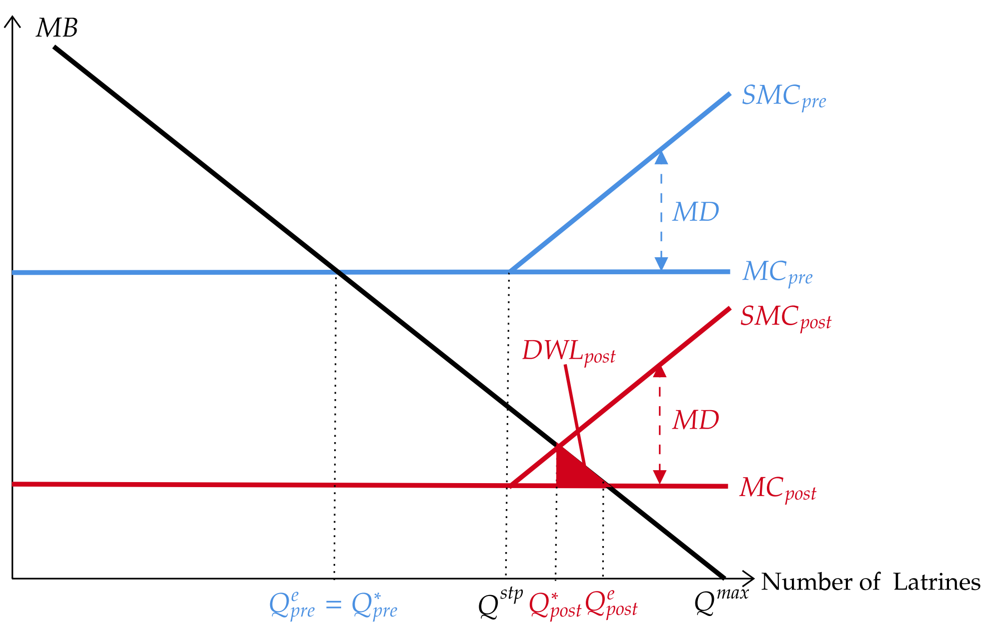
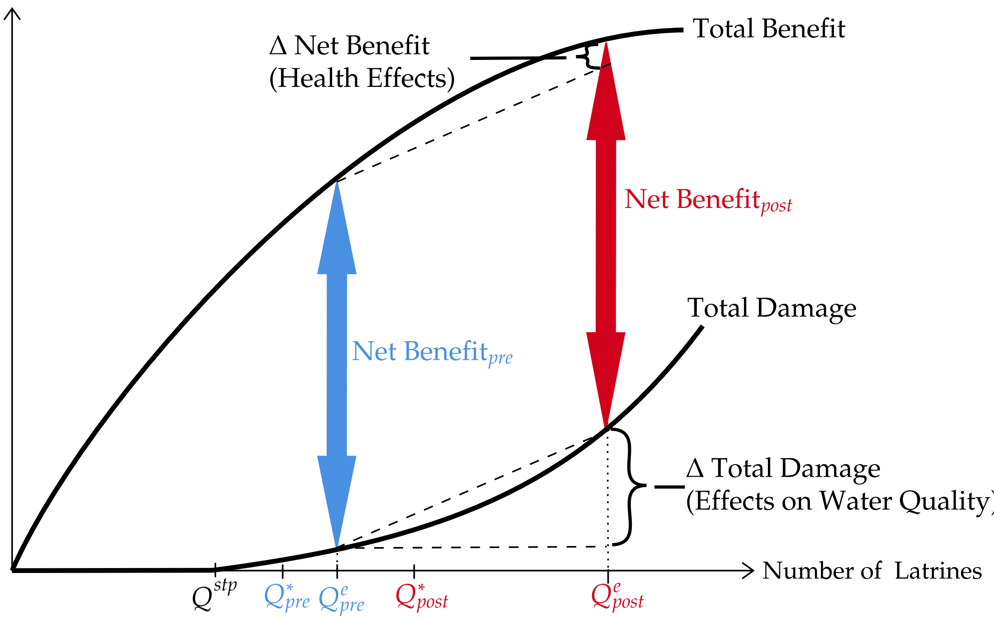


Figure A1: Welfare Effects of the Swachh Bharat Mission

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 from reduced open defecation. This figure shows that DWL increases more substantially in the case of low treatment capacity (Panel A) than in the case of high treatment capacity (Panel B).

Panel A. Treatment Capacity Low



Panel B. Treatment Capacity High

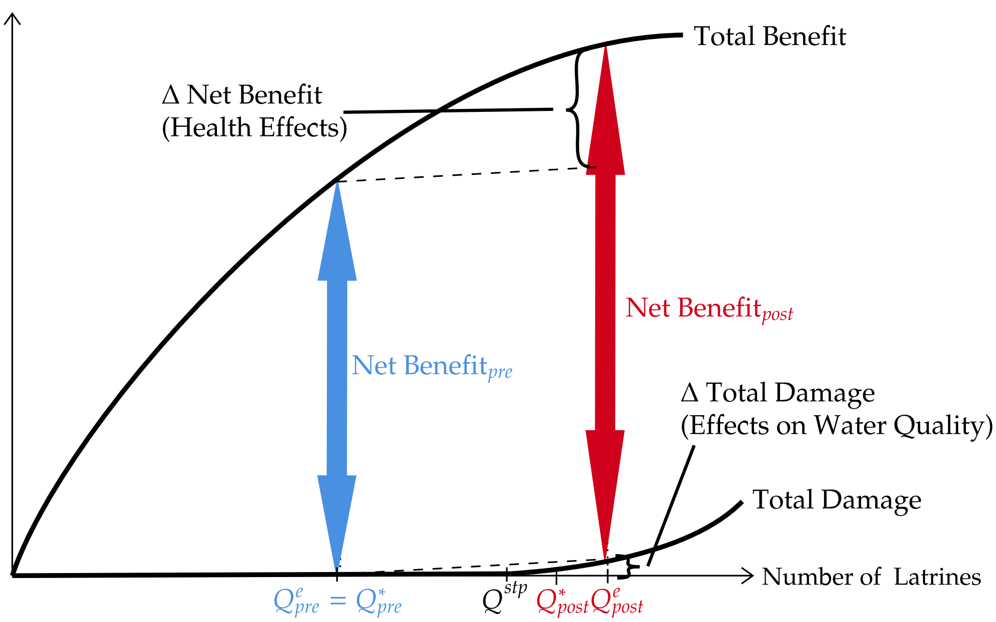


Figure A2: Effects of the Swachh Bharat Mission on Water Quality and Health

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}). The total benefit and total damage in this figure are based on the marginal benefit and marginal damage plotted in Appendix Figure A1. Effects on health and water quality are represented by the changes in net benefit and total damage, respectively. This figure shows that the 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, while the magnitude of water quality effects is larger.

B Data Appendix

B.1 Water Quality

- I obtain the monitoring 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 water body types: (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 data from the first and second types, encompassing all types of rivers.
- I use the yearly average values of the following water quality indicators in the analysis.
  - Fecal Coliform: Yearly maximum values are also used for the robustness check.
  - Nitrate and Nitrite, Temperature, Dissolved Oxygen, Biochemical Oxygen Demand (for falsification tests)
- I drop outliers of water temperature (one observation of over 100 °C) from the sample in the falsification tests.
- 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 boundary data and GPS location data of monitoring stations to identify districts where monitoring stations are located.

B.2 Health

- I obtain the 5 km raster data of mortality and overweight prevalence 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, 2020a)
`https://ghdx.healthdata.org/record/ihme-data/global-under-5-diarrhea-incidence-prevalence-mortality-geospatial-estimates-2000-2019` (accessed May 30, 2021)

2. Overweight Prevalence: Global Under-5 Overweight Prevalence Geospatial Estimates 2000-2019 (IHME, 2020b)
   `https://ghdx.healthdata.org/record/ihme-data/global-under-5-overweight-prevalence-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.
  - Diarrheal Mortality: India Demographic and Health Survey 2005–2006, 2015–2016, India District Level Household Survey 2002–2005, 2007–2008, 2012–2014, and India Human Development Survey 2004–2005, 2011–2013
  - Overweight Prevalence: India Coverage Evaluation Survey 2009-2010, India Demographic and Health Survey 2005–2006, 2015–2016, India District Level Household Survey 2002–2005, 2007–2008, 2012–2014, and India Human Development Survey 2004–2005, 2011–2013
- I use estimates of diarrheal mortality rates of five age groups, that is, early-neonatal (0–6 days), late-neonatal (7–27 days), post-neonatal (28–364 days), ages 1–4 years, and under 5 years. I also use estimates of overweight prevalence for ages 0–5 years.
- I use the mean estimates of mortality rates (per 1,000 children, or per child multiplied by 1,000) and overweight prevalence.
- For the analysis, I compute the district-level means of mortality rates and overweight prevalence estimates based on the raster data and 2011 district boundary data.
- As a robustness check, I adopt the following alternative mortality dataset.
  - National Family Health Survey 5 (NFHS-5) 2019-2021
    `https://dhsprogram.com/methodology/survey/survey-display-541.cfm`
    (accessed June 21, 2023)
  - The NFHS-5 interviews all women aged 15–49 years within the sample households and records detailed information about their birth histories.
  - In their birth histories, I use the data concerning the year of birth and whether the child died within 12 months of birth, that is, an infant mortality indicator. This

mortality indicator encompasses all types of mortality, not solely those driven by water pollution.

B.3 Latrines

- I obtain data on the number of constructed household latrines from 2012 to 2019 in rural India from the following official database of the SBM policy.
  - 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` (originally accessed March 28, 2020)
  - The format name and the URL have been updated as follows: ER 77: Swachh Bharat Mission Target Vs Achievement On the Basis of Detail entered `https://sbm.gov.in/sbmphase2/Secure/Entry/UserMenu.aspx` (accessed March 5, 2023)
- The raw tables scraped from this database 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 is divided into Districts B and C between 2011 and 2019, the number of latrines in District A is computed as the total number of latrines in Districts B and C. This aggregation allows me to match the latrine data with the water quality data based on the 2011 boundary.
- For the IV design, I compute the number of latrines per square kilometer by dividing the number of latrines by district area. The district area is computed using 2011 district boundary data.
- For the DiD design in the robustness check, 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.

B.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 the 2011 Census.
  - 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 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 m wide at mean annual discharge globally.
  - I use this river line data in robustness checks that adopt an alternative mortality dataset and conduct a health analysis in areas close to rivers.
- Digital Elevation Data
  - I obtain 90 m raster elevation data from the following database.
    * Shuttle Radar Topography Mission 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 districts.

B.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
    `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.

B.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 extract 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 heterogeneity analysis.

B.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/cmpg/Griddata/Rainfall_25_NetCDF.html` (accessed April 8, 2021)

  - First, I aggregate daily raw data into 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 DiD design in the robustness check, 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
  - For the DiD design in the robustness check, 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)

B.8 Identification of Upstream Districts

- I identify upstream districts for the upstream–downstream analysis, which is discussed in Section 4.2.
- 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 districts. Then, for the water quality data, I use 365 monitoring stations that are within 4 km of the major rivers. The district-level health analysis focuses on 103 districts that have monitoring stations along the major rivers.
- Second, I use elevation data along the major rivers to identify the upstream–downstream relationships between 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). This operation, aimed at identifying upstream districts, is repeated for each major river.

- If the major rivers have several branches, I divide them into smaller segments at each branching point. Ultimately, I decompose 43 major rivers into 60 segments, which I use to determine the upstream–downstream relationships.
- If two or more rivers flow through a given district, I do not include this district in the final sample because the upstream–downstream relationships become unclear.
- 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 $[X, Y]$ km from the given district (station), where $X \in \{0, 50, 100\}$, $Y \in \{100, 150\}$, and $X < Y$.

B.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 5.3.
- First, I identify monitoring stations that are situated in more than one district. I create 2 km buffers around stations and select stations whose buffers intersect with 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.

B.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 5.3.
- 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`).
- Finally, I drop monitoring stations and districts that are within 50, 100, or 150 km of the GPS locations of these cities in the robustness check.

C Robustness Check: Difference-in-Differences Design

As a robustness check, I adopt an alternative DiD design that exploits the differential increase in latrine coverage across districts with different baseline coverage levels.

C.1 Empirical Strategy

An alternative DiD design uses the district-level baseline latrine coverage as a treatment, which affects the number of latrines constructed under the SBM.[72] This design exploits the fact that all districts achieved almost universal latrine coverage by the 2019 target date, regardless of their baseline latrine coverage. Thus, districts with lower baseline latrine coverage experienced larger increases in latrine coverage. As shown in Appendix Figure C1, there were substantial differences in baseline latrine coverage across districts in 2013, suggesting a differential increase in the number of latrines by 2019. As expected, I find that lower baseline coverage is positively correlated with the number of latrines constructed under the SBM (Appendix Figure C2). I expect that districts with higher latrine non-coverage (lower latrine coverage) in 2013 experienced a greater increase in water pollution owing to a larger increase in latrine coverage.

In this alternative DiD design, I adopt the following regression:

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

where $Y_{i,d,t}$ is a water quality indicator, represented by the logarithm of fecal coliform, at monitoring station i located in district d in year t. $Latrine_d^{pre}$ is the latrine coverage in district d in 2013, one year before the SBM started. $Post_t$ is an indicator that takes the value of one after 2014, when the SBM started. $\mathbf{X_{d,t}}$ is a set of control variables, which are time-varying precipitation and time-invariant district characteristics, including VIIRS nighttime luminosity in 2013, population, proportions of Scheduled Caste and Scheduled Tribe members, and literacy rates in 2011. Time-invariant variables are added as control variables after interacting with the year dummies. Monitoring station fixed effects (δ_i) are included as per the IV design. Basin-year fixed effects ($\theta_{b,t}$) are also included to account for secular trends in water quality across years, which may vary across river basins. Standard errors are clustered at the district level because the baseline latrine coverage varies across

[72] This DiD design that uses variation in the baseline degree of policy implementation is in the same vein as Duflo (2001) and Bleakley (2007). While another potential approach could be to leverage variation in the timing of latrine construction initiation, this is challenging to implement because only one district had 0% baseline coverage in 2013, and most districts were already treated before the implementation of SBM.

districts. The coefficient of interest is β_{DID} and is expected to be positive; that is, a higher increase in water pollution.

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

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

where the reference year is set to 2013, and T_l is a year dummy variable. The standard errors are clustered similarly at the district level. The coefficient of interest is β_l, which measures the treatment effect on water quality for each year relative to 2013. The β_l's for 2007–2012 are examined to test the assumption of parallel pre-trends, whereas the β_l's for 2014–2019 capture the dynamic evolution of the treatment effects. Based on the tests of parallel pre-trends, I show the results of the DiD design only for water quality outcomes.

C.2 Data

The DiD design uses the same datasets for water quality and latrines introduced in Section 3. This design uses longer panel water quality data from 2007 to 2019. I additionally identify the basin of each monitoring station using the GPS coordinates of the monitoring stations and the "Watershed Map of India" of the ML Infomap. It also uses latrine coverage in 2013 as a treatment, which is computed by dividing the number of household latrines in 2013 by the total number of households recorded in each district.

This design uses two additional datasets to account for other district characteristics that affect latrine construction and water quality and achieve a better balance between the treatment and control groups.

First, I use 15 arc-second (<500 m at the equator) raster data of nighttime lights to account for the size of the economy at the district level. Specifically, I use the V.2 annual composites of the Visible and Infrared Imaging Suite Day Night Band (VIIRS DNB) (Elvidge et al., 2021).[73] The district-level mean nighttime luminosity in the pre-SBM period is computed based on the 2013 annual composite.

Second, 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 from the 2011 Census of India.

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

C.3 Results

As in the IV design, I find that latrine construction under the SBM increases river pollution, especially in areas with lower treatment capacities. The positive coefficient in Column 1 of Appendix Table C1 suggests that latrine construction increases water pollution, although the effect becomes imprecise in the DiD design. Heterogeneity analysis by fecal sludge treatment capacity confirms that the negative externality on water quality is concentrated in areas with lower treatment capacities (Columns 2–5). The coefficients of $(1 - Latrine_d^{pre}) \cdot Post_t$ show that a district with a 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 that the baseline latrine coverage was 39.2% in 2013, the total effects of the SBM in states with lower treatment capacities can be calculated as $(1 - 0.392) \times 1.790 = 1.088$, which is relatively close to the average policy effect (0.976) in Column 3 of Panel A of Table 4 in the IV design. Conversely, consistent with the results of the IV design, no negative externality is found in areas with higher treatment capacities (Columns 2 and 4).

The event study results show that the negative externality on water quality in areas with lower treatment capacities has become significant two years after the start of the SBM, and this effect has increased over time. The estimated coefficients of the event-study specification are reported in Appendix Figure C3. First, Appendix Figure C3 shows no differential pre-trends for most panels (except Panel D), which enhances the validity of the parallel pre-trends assumption. Second, Appendix Figure C3 highlights that the negative externality in states with lower treatment capacities has become significant since 2016, two years after the start of the SBM, and this effect has become larger from 2016 to 2019 (Panel B).[74] The lagged effect is consistent with the fact that the differential increase in the number of latrines among districts with different levels of baseline coverage began around 2016, as shown in Appendix Figure C2.

[74] Appendix Figure C3 also 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 D), I focus on the results based on state-level variations in treatment capacities.

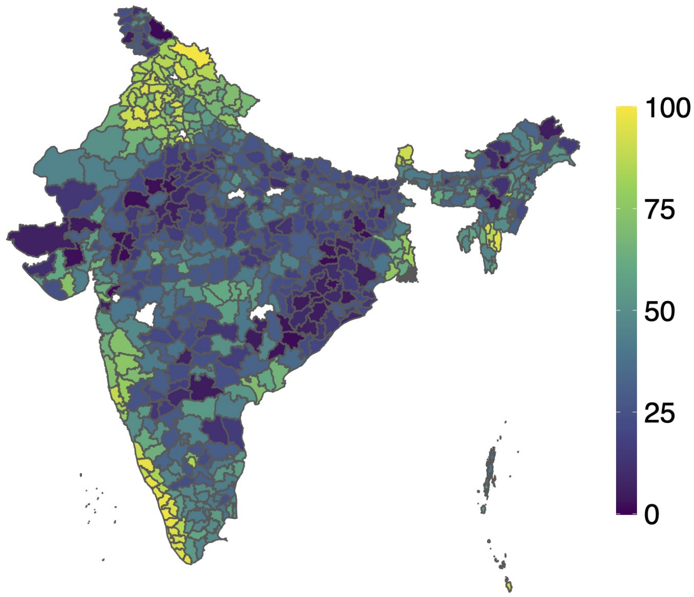


Figure C1: Latrine Coverage (%) in 2013 across Districts

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.

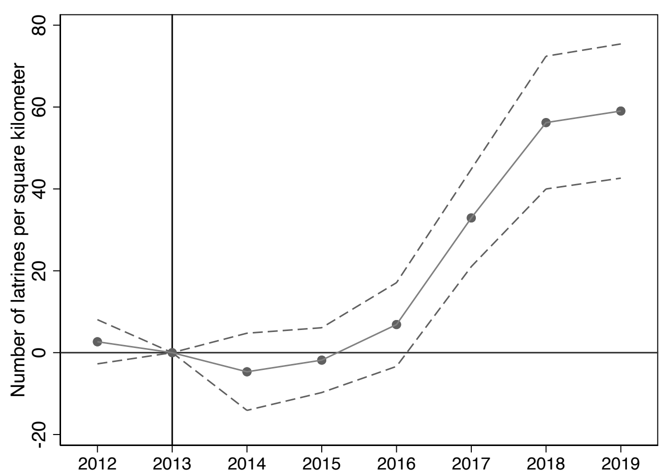


Figure C2: Differential Change in the Number of Latrines between Districts with Lower Baseline Coverage and Districts with Higher Baseline Coverage

Notes: This figure shows the district-level regression coefficients of the number of latrines per square kilometer on the interaction terms between (1- baseline latrine coverage in 2013) and year dummies. 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.

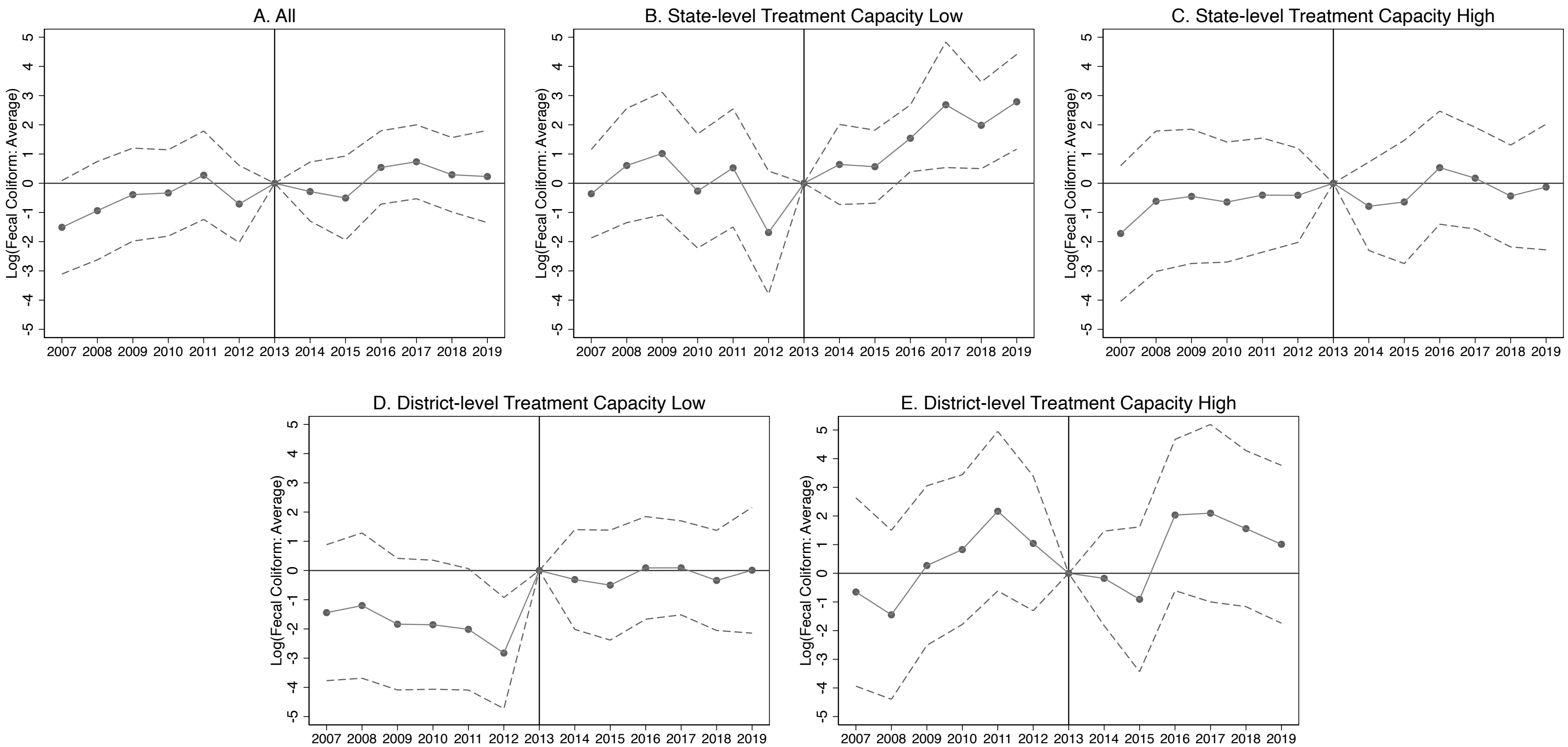


Figure C3: The Dynamic Effects on Water Pollution (Log of Fecal Coliform)

Notes: This figure shows the regression coefficients of the logarithm of fecal coliform in regression 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. Panel B shows a result in states where the treatment capacities of sewage treatment plants are lower than the median, while Panel C shows a result in states with higher treatment capacities. Panel D shows a result in districts where the treatment capacities are lower than the median, while Panel E shows a result in districts with higher treatment capacities.

Table C1: DiD Results: 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
(1 - 2013 Latrine Coverage) * Post (= 1)	0.647	0.372	1.790***	0.496	1.496**
	(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

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 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 the treatment capacities of sewage treatment plants are higher than the median, while Column 3 reports a result in states with lower treatment capacities. Columns 4 and 5 compare results based on the different levels of treatment capacities at the district level.

D Back-of-the-Envelope Cost-Benefit Analyses

D.1 Cost-Benefit Analysis of Swachh Bharat Mission

The district-level mortality benefit (USD 5.6 million) is calculated by multiplying the total number of mortalities reduced under the SBM (10.4) by the estimated value of a statistical life in India, which amounts to USD 0.54 million or INR 44.69 million (Majumder and Madheswaran, 2018).[75] The reduction in the total number of mortalities is calculated by multiplying the estimated average policy effect (0.269 per 1,000 children) by the estimated district-level mean population aged 0-1 (0.039 million people). This population estimate is derived from the district-level mean population (1.66 million people) and the percentage of the population aged 0-4 (9.32%), according to the 2011 Census. It is assumed that the population aged 0–1 constitutes one-fourth of the population aged 0–4.

The district-level subsidy cost (USD 16.9 million) is calculated by multiplying the amount of the SBM subsidy (USD 144.1 or INR 12,000) by the increased number of latrines at the district level between pre-SBM and post-SBM periods (0.12 million).

D.2 Cost-Benefit Analysis of Having Higher Treatment Capacity

The district-level additional benefit (USD 7.4 million) is calculated by multiplying the difference in the estimated average policy effects between districts with higher and lower treatment capacities (0.364-0.009=0.355 per 1,000 children) by the same value of a statistical life in India.

The district-level additional cost (USD 4.5 million) is calculated by multiplying the unit cost of sewage treatment plants (0.10 million USD/million liters per day), which consists of the capital cost and the operation and maintenance cost, by the district-level difference in STP capacity between districts with higher and lower treatment capacities (45.0 million liters per day). To construct the unit cost of sewage treatment plants, I refer to the estimates of the capital cost for secondary treatment (USD 0.03 million per million liters per day) and the operation and maintenance cost (USD 0.07 million per million liters per day) over a period of five years for the most commonly used technology, the Upflow Anaerobic Sludge Blanket, provided by the Central Pollution Control Board (CPCB, 2013). These five years correspond to the duration of the post-SBM period in the analysis. Assuming a 15-year lifespan for STPs, the five-year capital cost is set to one-third of the total capital cost.

[75] In the cost–benefit analysis, an exchange rate of USD 1 = 83.2 INR (or INR 1 = USD 0.012), as of November 9, 2023, is adopted.

E Additional Figures

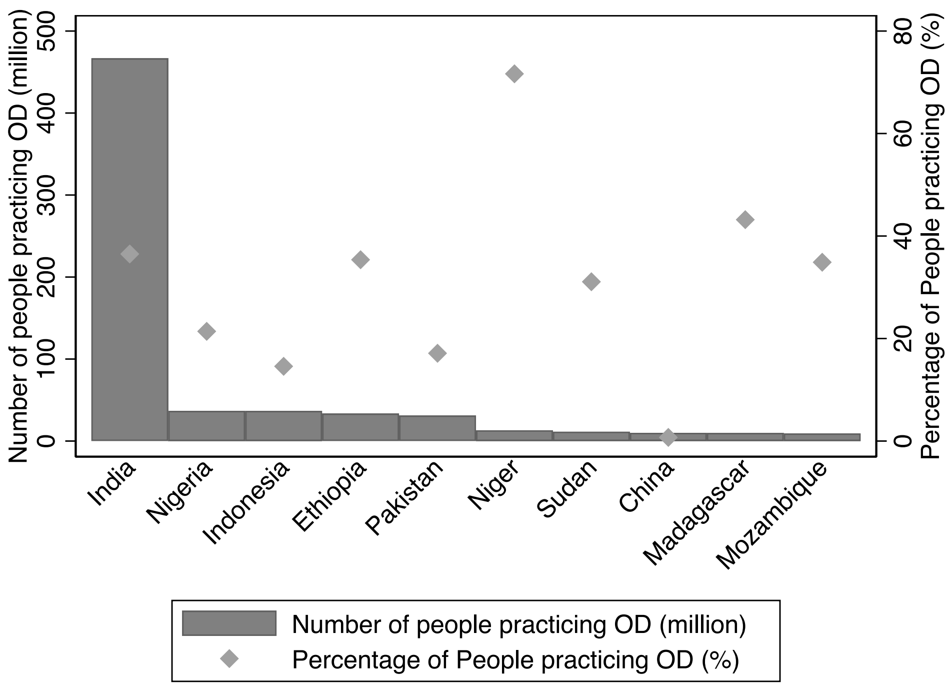


Figure E1: Top 10 Countries by the Number of People Practicing Open Defecation in 2013

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

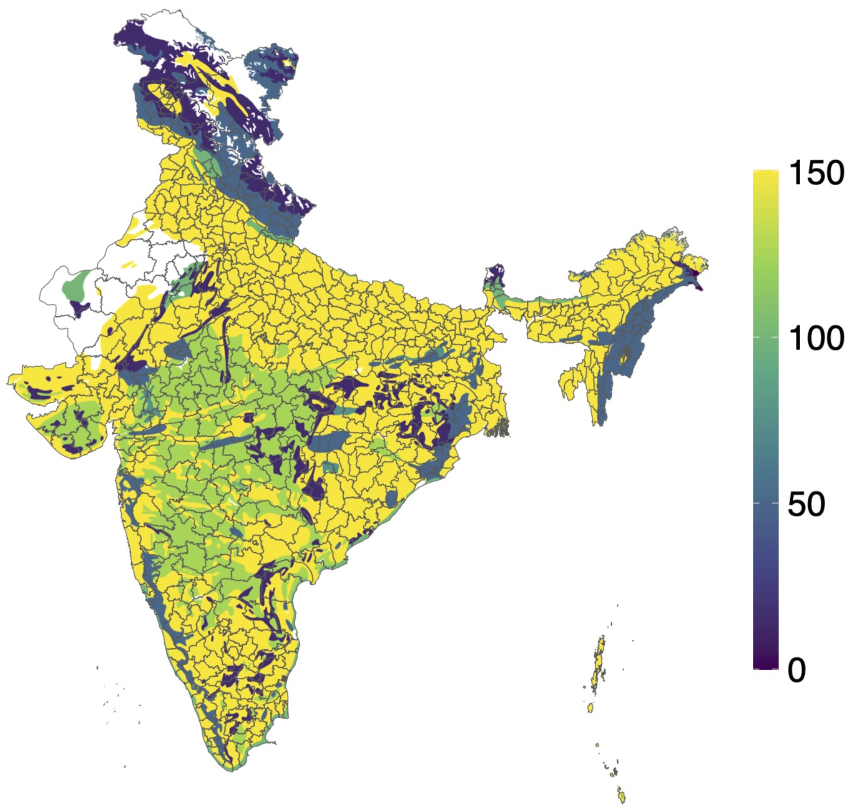


Figure E2: Distribution of Available Water Capacity (mm/m)

Notes: White areas indicate missing data on Available Water Capacity. These areas are not included in the final sample of the analysis due to the absence of water quality monitoring stations, as shown in Figure 2. District boundaries are depicted with black lines.

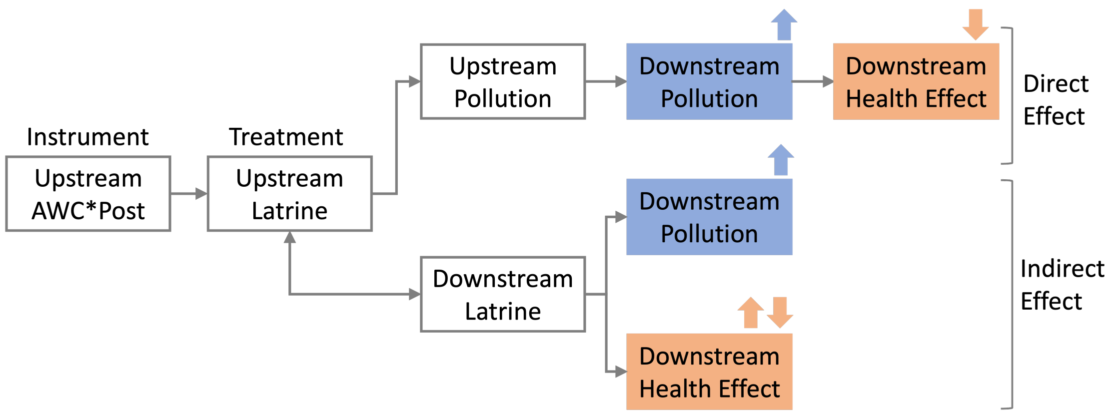


Figure E3: Two Underlying Channels in Upstream–Downstream Analysis

Notes: This figure illustrates two underlying channels in the upstream–downstream analysis. The β_{IV}^{U} in regression 3 represents the composite of the two underlying effects. In this figure, a reference district is referred to as a downstream area. The first underlying channel is a direct effect where upstream latrine construction leads to water pollution that flows downstream, subsequently causing a negative externality on health in downstream areas. The second underlying channel is an indirect effect where downstream latrine construction, which is correlated with upstream latrine construction, contributes to increased water pollution in downstream areas. The sign of the health effect in the second channel depends on the relative magnitude of direct positive health effects and water pollution externalities resulting from latrine construction (reduced open defecation) in downstream areas.

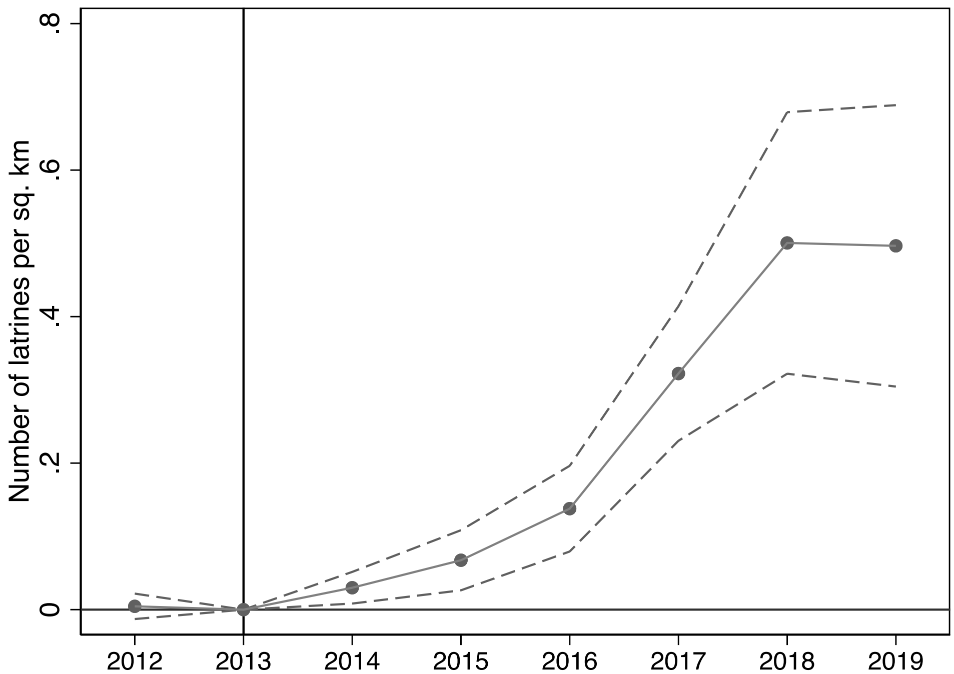


Figure E4: Event Study Plot of First-Stage Regression of Number of Latrines

Notes: This figure shows the regression coefficients of the number of latrines per square kilometer on the interaction terms between Available Water Capacity and year dummies in the water quality regression. The 95% confidence intervals are shown with dashed lines. Standard errors are clustered at the district level. The regression includes monitoring station fixed effects, year fixed effects, and precipitation as a control.

F Additional Tables

Table F1: Summary Statistics of Variables for Robustness Checks

	Mean	SD	Min	Max	Obs.
Panel A. Time-varying variables: pre-SBM (2007-2013)					
Fecal coliform: Maximum (million MPN/100ml)	5.21	287.55	0	20000	4939
Nitrate/Nitrite: Average (mg/L)	1.8	2.77	0	24.5	2436
Temperature: Average (°C)	24.79	4.79	2.9	43.5	5206
Biochemical Oxygen Demand: Average (mg/L)	5.4	17.17	0	534.5	5219
Dissolved Oxygen: Average (mg/L)	6.77	1.75	0	38.85	5204
Diarrheal early-neonatal mortality rate (per 1,000)	20.2	13.65	0.5	71.86	2359
Diarrheal late-neonatal mortality rate (per 1,000)	9.22	6.19	0.23	32.41	2359
Diarrheal age 1-4 mortality rate (per 1,000)	0.48	0.34	0.01	1.83	2359
Diarrheal under 5 mortality rate (per 1,000)	1.07	0.72	0.03	3.87	2359
Overweight prevalence age 0-5 (%)	6.77	2.33	0.77	17.57	2359
Infant mortality rate (per 1,000) $<$ 5 km of rivers	36.44	187.37	0	1000	63125
Infant mortality rate (per 1,000) $<$ 10 km of rivers	36.9	188.53	0	1000	101045
Latrine coverage (%)	43	25.48	0.08	100	586
Panel B. Time-varying variables: post-SBM (2014-2019)					
Fecal coliform: Maximum (million MPN/100ml)	1.44	60.76	0	3500	5555
Nitrate/Nitrite: Average (mg/L)	2.19	19.84	0	1150.02	5521
Temperature: Average (°C)	24.85	4.36	0	35	5765
Biochemical Oxygen Demand: Average (mg/L)	5.5	18.52	0	719.5	5739
Dissolved Oxygen: Average (mg/L)	6.61	1.81	0	51.1	5766
Diarrheal early-neonatal mortality rate (per 1,000)	9.79	7.28	0.29	35.57	2022
Diarrheal late-neonatal mortality rate (per 1,000)	4.64	3.44	0.14	16.76	2022
Diarrheal age 1-4 mortality rate (per 1,000)	0.2	0.15	0.01	0.73	2022
Diarrheal under 5 mortality rate (per 1,000)	0.51	0.38	0.02	1.86	2022
Overweight prevalence age 0-5 (%)	7.35	2.73	0.57	25.49	2022
Infant mortality rate (per 1,000) $<$ 5 km of rivers	34.45	182.38	0	1000	41946
Infant mortality rate (per 1,000) $<$ 10 km of rivers	35.31	184.56	0	1000	67633
Latrine coverage (%)	76.78	27.43	3.58	100	1814
Panel C. Variables not varying over time					
2011 Population (thousand)	1572.08	1077	28.99	6074.19	337
2011 % of Scheduled caste population	16.75	9.69	0	53.39	337
2011 % of Scheduled tribe population	16.98	25.24	0	98.10	337
2011 % of Literate population	61.16	10.44	28.66	88.7	337
2013 VIIRS nighttime luminosity (nW/cm2/sr)	0.71	1.57	0.01	17.98	337

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 to 2019, while data of other time-varying variables are available from 2007 to 2019.

Table F2: Balance Tests between Sample Districts and Remaining Districts in India

	Means: pre-SBM				Differences		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	All	Baseline	U–D (Water)	U–D (Health)	(2) vs not (2)	(3) vs not (3)	(4) vs not (4)
Latrine coverage (%)	40.42	42.11	39.72	39.42	3.75*	-0.93	-1.19
	(25.14)	(25.58)	(23.32)	(21.77)	(2.02)	(2.23)	(2.42)
Diarrheal post-neonatal	2.32	2.19	2.52	2.50	-0.27*	0.26*	0.22
mortality rate (per 1,000)	(1.93)	(1.52)	(1.56)	(1.61)	(0.16)	(0.16)	(0.18)
Population (thousand)	1302.73	1572.08	1723.64	1657.13	568.91***	554.28***	422.37***
	(1018.81)	(1077.00)	(1029.35)	(996.05)	(76.60)	(93.98)	(107.10)
VIIRS nighttime	1.36	0.71	0.67	0.66	-1.38***	-0.91***	-0.84***
luminosity (nW/cm2/sr)	(5.39)	(1.57)	(0.86)	(0.91)	(0.44)	(0.29)	(0.27)

Notes: Columns 1-4 report the means of pre-SBM variables (in 2013, except for population in 2011) for the baseline sample, the upstream–downstream sample for water quality analysis, and the upstream–downstream sample for health analysis, respectively. Columns 5-7 test the differences between each sample and the remaining districts in India, with ***, **, and * indicating significance at the 1%, 5%, and 10% levels, respectively.

Table F3: Upstream–Downstream Analysis: Alternative Buffer Sizes

	Buffer Distances from Reference Stations/Districts					
	(1) 0–50 km	(2) 0–100 km	(3) 0–150 km	(4) 50–150 km	(5) 100–150 km	(6) Full
Panel A. Dependent Variable: Log(Fecal Coliform)						
Upstream number of latrines per sq. km	0.014	0.017	0.015	0.003	0.001	0.037**
	(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]
Average Policy Effect	0.427	0.481	0.431	0.098	0.021	0.754
Panel B. Dependent Variable: Diarrheal Post-neonatal Mortality Rate (per 1,000)						
Upstream number of latrines per sq. km	-0.011*	-0.012*	-0.011*	-0.012*	-0.017***	0.003
	(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
Average Policy Effect	-0.309	-0.294	-0.269	-0.303	-0.458	0.049

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, buffer sizes are changed to identify upstream districts. In Column 6, all upstream districts are included without the restriction on buffer sizes. Regressions in Panel A include monitoring station fixed effects, year fixed effects, and the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district. Regressions in Panel B include district fixed effects, year fixed effects, and the same controls as in 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. The means of dependent variables are calculated for the pre-SBM period. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table F4: Falsification Tests

	Log(Nitrate/Nitrite)		Log(Temperature)		Log(BOD)		Log(DO)		Overweight Prevalence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Number of latrines per sq. km	0.0003 (0.0162)		-0.0021 (0.0014)		-0.0034 (0.0037)		-0.0008 (0.0010)		
Upstream number of latrines per sq. km		0.0205 (0.0147)		-0.0022* (0.0012)		0.0048 (0.0058)		-0.0006 (0.0010)	-0.0131 (0.0184)
Observations	6,379	1,848	7,102	2,171	7,084	2,191	7,094	2,205	824
Number of Stations	1,142	341	1,179	359	1,184	364	1,181	364	-
Number of Districts	319	142	334	151	336	153	336	153	103
KP F-Stat	7.991	44.278	28.449	47.154	28.067	47.218	29.955	50.664	78.696
AR 95% CI	[... , .033]	[-.017, .052]	[-.005, .001]	[-.006, .000]	[-.011, .005]	[-.007, .018]	[-.003, .001]	[-.003, .002]	[-.050, .027]
Mean of Dep. Variable	2.110	1.633	24.775	24.543	5.157	3.361	6.653	7.205	6.781

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 in Columns 1, 3, 5, and 7 include monitoring station fixed effects, year fixed effects, and precipitation as a control. Regressions in Columns 2, 4, 6, 8, and 9 include monitoring station (or district) fixed effects, year fixed effects, and the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district, and upstream districts are defined as those within the range of $[0, 150]$ km from a reference district. Column 9 uses overweight prevalence (%) for ages 0–5 as an outcome. 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 95%. The means of dependent variables are calculated for the pre-SBM period.

Table F5: The Effect on Log of Maximum Values of Fecal Coliform

	All	State-level Capacity		District-level Capacity	
	(1)	(2)	(3)	(4)	(5)
	All	High	Low	High	Low
Number of latrines	0.033***	-0.033	0.040***	0.016*	0.055***
per sq. km	(0.009)	(0.026)	(0.007)	(0.010)	(0.018)
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	[.017, .054]	[-.130, .018]	[.028, .059]	[-.010, .038]	[.026, .114]
Average Policy Effect	0.801	-0.715	1.069	0.340	1.463

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 monitoring station fixed effects, year fixed effects, and precipitation as a control. Column 2 reports a result in states where the 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. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table F6: The Effect on Log of Fecal Coliform After Removing Outliers

	Cutoff Percentiles for Removing Outliers			
	(1) 99 Percentile	(2) 95 Percentile	(3) 90 Percentile	(4) 75 Percentile
Number of latrines per sq. km	0.030*** (0.008)	0.033*** (0.008)	0.032*** (0.008)	0.036*** (0.014)
Observations	7,124	6,828	6,455	5,321
Number of Stations	1,183	1,148	1,113	967
Number of Districts	334	330	323	290
KP F-Stat	29.124	26.142	35.480	38.309
AR 95% CI	[.015, .050]	[.018, .055]	[.018, .050]	[.007, .069]
Average Policy Effect	0.724	0.755	0.754	0.629

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 monitoring station fixed effects, year fixed effects, and precipitation as a control. Columns 1–4 report results after removing outliers of fecal coliform values above the 99th, 95th, 90th, and 75th percentiles, respectively. 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 between pre-SBM and post-SBM periods.

Table F7: The Effects on Diarrheal Mortality Rates of Other Age Groups (per 1,000)

	(1) Early-neonatal	(2) Late-neonatal	(3) Post-neonatal	(4) Age 1–4	(5) Under 5
Upstream number of latrines per sq. km	-0.092** (0.046)	-0.042* (0.021)	-0.011* (0.006)	-0.002** (0.001)	-0.005** (0.002)
Observations	824	824	824	824	824
Number of Districts	103	103	103	103	103
KP F-Stat	78.696	78.696	78.696	78.696	78.696
AR 95% CI	[-.190, .005]	[-.086, .003]	[-.023, .001]	[-.005, .000]	[-.010, .000]
Mean of Dep. Variable	18.562	8.656	2.576	0.411	0.969
Average Policy Effect	-2.221	-1.004	-0.269	-0.057	-0.116

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 the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district. The sample is limited to districts that have monitoring stations used in the water quality regression along major rivers in India. Upstream districts are defined as those within the range of $[0, 150]$ km from a reference district. 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 means of dependent variables are calculated for the pre-SBM period. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table F8: 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
Number of latrines	0.027***	-0.027	0.037***	0.017*	0.043***
per sq. km	(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

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 monitoring station fixed effects, year fixed effects, and precipitation as a control. Column 2 reports a result in states where the treatment capacities of sewage treatment plants are higher than the median, while Column 3 reports a result in states with lower treatment capacities. 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. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table F9: Robustness Check - Influence from Urban Areas

	No Exclusion	50 km Exclusion	100 km Exclusion	150 km Exclusion
	(1)	(2)	(3)	(4)
Panel A. Dependent Variable: Log(Fecal Coliform)				
Number of latrines per sq. km	0.030***	0.039***	0.050***	0.072**
	(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 Rate (per 1,000)				
Upstream number of latrines per sq. km	-0.011*	-0.010	-0.007	-0.009
	(0.006)	(0.008)	(0.011)	(0.015)
Observations	824	480	288	152
Number of Districts	103	60	36	19
KP F-Stat	78.696	49.232	22.506	29.583
AR 95% CI	[-.023, .001]	[-.026, .008]	[-.031, .025]	[-.045, .042]
Mean of Dep. Variable	2.576	2.577	2.561	2.670
Average Policy Effect	-0.269	-0.208	-0.150	-0.137

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 or more. 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 the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district, and upstream districts are defined as those within the range of $[0, 150]$ km from a reference district. 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 95%. The means of dependent variables are calculated for the pre-SBM period. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table F10: 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
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

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. All regressions include monitoring station fixed effects, year fixed effects, and precipitation as a control. Column 2 reports a result in states where the 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 95%. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table F11: Robustness Check - Alternative Mortality Dataset: The Effects on Health of Children Living Close to Rivers (Infant Mortality Rate (per 1,000))

	All	State-level Capacity		District-level Capacity	
	(1)	(2)	(3)	(4)	(5)
	All	High	Low	High	Low
Panel A. Children Living within 5 km of Rivers					
Upstream number of latrines per sq. km	-1.954***	-4.022**	-1.399**	-2.386***	-1.652
	(0.579)	(1.966)	(0.551)	(0.685)	(1.066)
Observations	11,034	5,677	5,357	5,358	5,676
Number of Districts	69	38	31	36	33
KP F-Stat	34.851	7.143	30.501	29.117	10.342
Mean of Dep. Variable	35.473	41.290	7.912	39.531	31.808
Panel B. Children Living within 10 km of Rivers					
Upstream number of latrines per sq. km	-1.251**	-3.195*	-0.839**	-1.769***	-0.821
	(0.481)	(1.842)	(0.395)	(0.603)	(0.780)
Observations	18,094	9,417	8,677	8,902	9,192
Number of Districts	70	38	32	36	34
KP F-Stat	37.937	7.894	30.501	32.344	9.160
Mean of Dep. Variable	36.321	37.710	9.356	40.404	32.579

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 the following controls: precipitation, the interaction of Available Water Capacity and the post-SBM indicator of a reference district, indicators for being a first-born child and part of a multiple birth, religion (Hindu, Muslim, others), caste (Scheduled Caste, Scheduled Tribe, Other Backward Class, others), education (primary, secondary, or higher), and wealth quintiles. Upstream districts are defined as those within the range of $[0, 150]$ km from a reference district. Column 2 reports a result when upstream states have higher treatment capacities of sewage treatment plants than the median, while Column 3 reports a result in the case of upstream states with lower treatment capacities. Columns 4 and 5 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 means of dependent variables are calculated for the pre-SBM period. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.

Table F12: Robustness Check - The Effects on Health in Areas Close to Rivers

	All	State-level Capacity		District-level Capacity	
	(1)	(2)	(3)	(4)	(5)
	All	High	Low	High	Low
Panel A. Diarrheal Post-neonatal Mortality Rate (per 1,000) within 5 km of Rivers					
Upstream number of latrines per sq. km	-0.010*	-0.038***	-0.010	-0.014**	0.000
	(0.006)	(0.011)	(0.006)	(0.007)	(0.010)
Observations	824	432	392	456	368
Number of Districts	103	54	49	57	46
KP F-Stat	78.696	33.304	33.484	59.873	18.756
AR 95% CI	[-.022, .002]	[-.073, -.020]	[-.025, .001]	[-.029, .000]	[-.027, .026]
Mean of Dep. Variable	2.569	2.530	2.612	2.423	2.750
Panel B. Diarrheal Post-neonatal Mortality Rate (per 1,000) within 10 km of Rivers					
Upstream number of latrines per sq. km	-0.011*	-0.039***	-0.010	-0.014**	0.000
	(0.006)	(0.011)	(0.006)	(0.007)	(0.010)
Observations	824	432	392	456	368
Number of Districts	103	54	49	57	46
KP F-Stat	78.696	33.304	33.484	59.873	18.756
AR 95% CI	[-.023, .001]	[-.073, -.022]	[-.026, .002]	[-.030, .000]	[-.028, .027]
Mean of Dep. Variable	2.576	2.540	2.616	2.430	2.758

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 the following controls: precipitation and the interaction of Available Water Capacity and the post-SBM indicator of a reference district. Upstream districts are defined as those within the range of $[0, 150]$ km from a reference district. Column 2 reports results when upstream states have higher treatment capacities of sewage treatment plants than the median, while Column 3 reports results in the case of upstream states with lower treatment capacities. Columns 4 and 5 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 means of dependent variables are calculated for the pre-SBM period. Average policy effects are calculated by multiplying the estimated coefficients by the change in the number of latrines per square kilometer between pre-SBM and post-SBM periods.