Monitoring Technologies, Environmental Performance, and Health Outcomes: Evidence from China

Zhilin Hu, Haoyang Li, Liguo Lin, Wei Sun, Maigeng Zhou

Abstract: In this study, we take the establishment of automatic surface water quality monitoring stations (automatic stations) in China as an example to explore the effects of adopting advanced monitoring technologies in enforcing environmental regulations. Automatic stations use real-time water quality monitoring and electronic-reporting technologies to go beyond traditional field inspection and monitoring and create novel enforcement approaches. We show that the establishment of downstream automatic stations significantly restrains industrial water pollution discharged and benefits human health. Specifically, the establishment of downstream automatic stations reduces wastewater emissions from upstream counties by 22%. Consequently, the death rate from digestive diseases decreases by 2.26 persons per 10,000 population and the life expectancy at birth increases by 3.14 years with the establishment of downstream automatic stations. This study provides clear evidence that advanced monitoring technology improves enforcement of environmental regulations, which brings significant health benefits and enhances social welfare.

JEL Codes: C33, K32, Q58

Keywords: automatic surface water quality monitoring stations, surface water quality, environmental regulations, digestive disease death rate, China

WIDER USE OF ADVANCED TECHNOLOGIES can improve the enforcement of environmental regulations. The advanced technologies, for instance, include automated instruments capable of collecting real-time information on emissions or ambient environmental

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quality and information technologies that allow the information to be collected, transmitted, and reported in real time. The increased transparency, because of applying real-time information and electronic-reporting technologies, results in novel enforcement approaches that go beyond traditional field inspections and provide opportunities for better compliance results and, therefore, better environmental outcomes.

In this study, we take the establishment of national automatic surface water quality monitoring stations (automatic stations) in China as a quasi-experiment to explore the effects of adopting advanced monitoring technologies on environmental policy enforcement and public health. Without efficient enforcement and monitoring, imposing environmental regulations does not necessarily lead to a reduction in pollution. The Environmental Protection Law and related environmental regulations in China all point out that local governments at or above the county level are legally responsible for the ambient environmental quality in their jurisdiction.[1] However, ambient environmental quality information is manually collected by local environmental protection agencies (EPAs) and then reported to the central government. Because of the focus on economic performance in local officials' promotion tournament (Li and Zhou 2005), local officials are incentivized to relax environmental regulation enforcement to induce economic growth while instigating local EPAs to manipulate the manually collected environmental data. This "race to the bottom" in environmental performance (Lin and Sun 2016) is largely accountable for the continuous deterioration of ambient environmental quality in China that has resulted in great public health problems (Ebenstein 2012; Chen et al. 2013).[2]

In particular, we show that the establishment of automatic stations in China (i.e., the adoption of real-time water quality monitoring and electronic reporting technologies) significantly decreases water pollution discharged in their upstream areas, the areas that are directly monitored by downstream automatic stations. To be specific, the establishment

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1. For example, the Law on Prevention and Control of Water Pollution (first enacted in 1984) and the Law on Prevention and Control of Atmospheric Pollution (first enacted in 1988).

2. According to the World Bank (2007), roughly 70% of the river water in China is unsafe for human consumption.

of downstream automatic stations decreases wastewater emissions from upstream counties by 22%. Consequently, public health is significantly improved. In particular, the death rate of digestive diseases decreases by 2.26 percentage points, and the life expectancy at birth increases by 3.14 years. In contrast, the death rates of other diseases that are less directly linked to water quality are largely unaffected. These results hold after a few robust tests. Given the nontrivial share of deaths from digestive diseases,[3] however, the importance of water-purifying infrastructure and the provision of clean water, such as tap water, still cannot be ignored in developing countries without effective enforcement of water pollution regulation. From another angle, individuals without access to clean drinking water sources should pay more attention to the prevention of digestive diseases.

The principle-agent problem created by imperfect monitoring and enforcement implies that local implementation of environmental regulations enacted by the central government can deviate from the social optimum (Lin 2013). From the change in industrial wastewater emissions following the establishment of automatic water monitoring stations, we document both implicitly and explicitly the data manipulation problem of manual stations. The increased enforcement capability of automatic stations thus helps align the incentives of central and local governments, pulling local environmental regulation implementation closer to the social optimum. The National Twelfth and Thirteenth Five-Year Plans (2011–20) for Ecological and Environmental Protection indicate that automatic real-time monitoring systems should be installed more widely in national environmental monitoring networks. A rough benefit-cost analysis based on our estimation results implies that the benefit of establishing automatic stations surpasses the cost by a wide margin, implying that the recent expansion of the automatic monitoring network has brought considerable welfare gain across the country. Our finding provides a clear policy implication, especially for developing countries where enforcement is usually weak and environmental quality is low: investing in advanced environmental monitoring technologies to strengthen the enforcement of current environmental policies may represent an effective yet low-cost option before enacting new and stricter regulations.

To go a step further, a more general policy implication is that permitting transparent public involvement in policy enforcement may achieve considerable environmental benefits with acceptable costs. Examples include making monitoring data publicly available or allowing the public to directly report environmental law violations that are made possible under the River Chief policy and the top-down Inspection of Environmental Regulations in China (Hu 2022).

Besides the efficiency implications above, we also document that larger benefits of establishing automatic stations have been accrued to regions with a low tap water coverage rate, which implies that the expansion of the automatic station network helps to improve regional equality from the perspective of regional public health.

3. Deaths from digestive diseases account for around 58% of all noninjury deaths in China.

Our study contributes to the literature in three ways. First, many existent studies have found evidence on manipulation of self-reported air pollution data by cities for the purpose of increasing "blue-sky days." Specifically, a day is counted as a "blue-sky day" for a city if the reported air pollution index (API) is below 100. Andrews (2008) presents evidence that the API in Beijing has massive bunching below the cut-off in addition to other gimmicks to falsify air quality reports in the local government's favor. Chen et al. (2012) find an anomaly around the cut-off based on the official API data from 37 large cities. Ghanem and Zhang (2014) further find that approximately 50% of 113 cities reported dubious PM_{10} pollution levels over the period 2001–10 that led to a discontinuity in the distribution of API at the cut-off level. Government officials also falsify surface water quality monitoring data. He et al. (2012) mention that upstream reservoirs deplete water to dilute water pollutant concentrations somewhere just before the sampling by downstream monitoring activities, and therefore, better water quality is reported. We directly test for the manipulation problem with readings from both manual and automatic stations that are placed in the same locations.

Second, most studies in the environmental regulation literature have attempted to develop efficient environmental enforcement and monitoring strategies to enhance compliance despite the limited inspections, monitoring resources, and effort. For instance, it was shown that state-dependent dynamic monitoring strategies that allow for differential monitoring probabilities in accordance with previous (or self-reported) compliance statuses would improve enforcement and compliance results (e.g., Harrington 1988; Harford 1991; Bayer and Cowell 2009; Gilpatric et al. 2011). With the adoption of automatic monitoring technologies, monitoring capacities are then largely expanded, which makes the monitoring strategies suggested obsolete. The US EPA mentions that emerging technologies result in traditional enforcement and compliance into the next generation that comprises a few interconnected components, such as advanced pollutant-detection technology, electronic reporting, and information transparency.[4] This study is one of few attempts to explore and evaluate the effects of adopting advanced environmental monitoring technologies on enforcing environmental regulations.

Finally, this study also contributes to the literature on the health impact of environmental regulations. Most of the studies in this literature have focused on developed countries (e.g., Chay and Greenstone 2003; Currie and Neidell 2005; Luechinger 2014), with a few exceptions. For example, Tanaka (2015) investigates the effect of environmental regulations pertaining to air pollution on infant mortality in China, and Greenstone and Hanna (2014) examine the effect of environmental regulations on air pollution, water pollution, and infant mortality in India.

Different from most studies in this literature, our study investigates the health impact of improved environmental regulation enforcement brought by the adoption of

4. See https://www.epa.gov/compliance/next-generation-compliance.

advanced monitoring technologies in a fast-growing developing country using a quasi-experimental design. Importantly, we show that environmental regulations alone may not achieve significant health benefits. In the information era, enhancing environmental monitoring capability with advanced information technologies may considerably enhance the effectiveness of environmental regulations. Except for Greenstone and Hanna (2014), empirical evidence derived from quasi-experimental designs on the health impact of water quality is still limited, especially in developing countries. While Greenstone and Hanna (2014) conclude that "water regulations had no measurable benefits" in India due in part to loose enforcement, our study quantifies nontrivial health benefits for the full population from enforcing water regulations by adopting advanced monitoring technologies in China. The comparison, therefore, implicitly manifests the importance of enforcement in achieving effective environmental regulation.

The remainder of the paper proceeds as follows. We begin in section 1 by reviewing the institutional background. Section 2 discusses the research questions. In section 3, we assess whether the establishment of automatic stations leads to decreases in the water pollution emitted by the industrial sectors. Section 4 investigates the effects of the establishment of automatic stations on public health, and section 5 concludes.

1. INSTITUTIONAL BACKGROUND

1.1. Water Pollution Prevention and Control

The first law aiming to control water pollution and protect surface water qualities was enacted in 1984 (Law on Prevention and Control of Water Pollution, LPCWP). The LPCWP states that local governments at or above the county level should add water resource protection into economic and social development planning, prevent and treat water pollution, and be responsible for the quality of the water in their regions of administration. The LPCWP further notes that the environmental protection administrative department of the State Council (i.e., Ministry of Ecology and Environment [MEE]). shall formulate the water quality standards and implement a water pollution prevention and control plan.

For the purpose of implementing and enforcing the LPCWP, the surface water quality grading classification standards were first issued in 1983 and amended in 1988, 1999, and 2002. Based on concentrations of pollutants in water bodies, water quality is evaluated on six graded scales from the best to the worse: the source of water bodies and national nature reserves (Grade I), drinkable water (Grade II), water undrinkable but suitable for aquaculture activities and human contact (Grade III), water suitable for industrial water supply and recreational waters but not direct human contact (Grade IV), water suitable for only agricultural irrigation and general landscape requirements (Grade V), and water that is essentially useless (Grade V+).

With the rapid growth of the economy, water pollution is becoming increasingly prominent in China. According to the 2005 Report on the State of the Environment, water quality in about 59% of water bodies in main river basins was rated Grade IV and above. In some river basins, over 50% of water bodies were rated Grade V+. The severe water quality deterioration results in great health costs. Ebenstein (2012) estimates that a deterioration of water quality by a single grade increases the digestive cancer death rate by 9.7%.

The increasing seriousness of water pollution pushes the central government to strengthen its efforts to control and remedy water pollution. A comprehensive suite of laws governing pollution prevention and remediation has been enacted, and the State Council set detailed objectives for local water managers in five year plans. For example, the objective of the ninth five-year plan for water pollution prevention and control in the Huai river basin (1996–2000) is to set water quality to reach the Grade III standard for the river's main stream and the Grade IV standard for the major tributaries; in its tenth five-year plan (2001–5), the quality grade objective is further elaborated regarding segments of the main stream and major tributaries; in its eleventh five-year plan, the Grade III standard objective is applied to most segments of the major tributaries. According to the water pollution prevention and control plan in the twelfth five-year plan (2010–15), the aim is to improve overall water quality in all key river/lake basins from moderately polluted to slightly polluted, increasing the Grade I–III water bodies by 5% while reducing Grade V+ water bodies by 8%.

To achieve the quality standard objectives, the plan further formulates the ceiling levels of major pollutants discharged to each river/lake basin. For instance, in the Huai river basin, the permitted total amount of chemical oxygen demand (COD) discharged is 2.46 million tons during 2010–15, reducing it by 11.2% from its 2010 level. These discharge control targets are then decomposed to relevant provinces and further to local regions. The plan also requires local regions to take various water pollution control measures, for example, closing water-pollution-intensive small-scale factories, prohibiting the establishment of new water-pollution-intensive small-scale factories; urging water-pollution-intensive factories to adopt cleaner production technologies and processes; assessing the impact of establishing new water-pollution-intensive factories on ambient water quality; prohibiting the establishment of new water-pollution-intensive factories in the regions where the discharge control targets are not achieved; and so forth. Following approval from the State Council, the plan is then issued to local provincial governments for implementation.

Although the plan provides detailed quality standard objectives, and specific pollution discharge targets, the implementation and enforcement at the local level are major problems. To enforce these policies, the State Council and MEE must monitor surface water quality, for which the national surface water quality-monitoring network is responsible.

1.2. National Surface Water Quality Monitoring Network

China's national surface water quality monitoring network is under the administration of China's national environmental monitoring center (CNEMC). The CNEMC is affiliated with the MEE, and its responsibilities include, for example, monitoring, assessing, and reporting the country's environmental ambient quality; providing technical supports for major pollution incident treatment; and accrediting laboratories of provincial monitoring centers.

The national surface water quality monitoring network was first established by the CNEMC in 1988, based on the hydrometric station network established by the Ministry of Water Resources, and comprised 379 monitoring sites along the country's major rivers and lakes. At these sites, monitoring activities are delegated to local Environmental Protection Bureaus (EPBs). These activities include manual water sampling and laboratory chemical contaminant analyses, based on which water quality information is reported to Provincial Environmental Monitoring Centers (PEMC) and to CNEMC. These sites are so-called state-controlled water quality monitoring sections.[5] We label these sites "manual surface water quality monitoring stations" (manual stations) to distinguish them from automatic stations. Since 2003, the manual station network has been largely extended: 759 sites are located on 318 rivers and 26 lakes/reservoirs, including 10 key river/lake basin subnetworks. Monitoring activities are conducted once per month and usually occur at the beginning of the month.

The location choice of monitoring sites mainly considers hydrological features of river basins and administrative regions.[6] For instance, monitoring sites are frequently located where major tributaries of major rivers or lakes flow into their main streams to monitor the fluctuation of water quality caused by the tributary inflows. Monitoring sites are also often located near boundaries of administrative regions, facilitating evaluating regional governments' performance in water pollution control, because the water pollution prevention and control plans are formulated on the basis of administrative regions. In particular, the sites are often located near upstream boundaries of administrative regions to monitor inflow water quality, which helps in clearing the responsibility of transboundary pollution and therefore in improving the evaluation of the performance of upstream regional governments in water pollution control.

In addition to the manual station network, the CNEMC started building automatic stations in 1999. The CNEMC first built 10 automatic stations on the Songhua River, Huai River, Yangtze River, Yellow River, and Lake Tai as a trial operation. One year later, in 2000, the network was formally launched, and the first 32 automatic stations were established. Since then, the automatic station network has been gradually expanded.

5. The sections are cross-sections of water bodies. From the official data, we know the county where a cross-section is located. The data do not report, however, the exact geographical coordinates of the cross-sections. In some cases, the reported location of a cross-section is a bridge or a dam in a county. We can then check the exact geographical coordinates of these cross-sections using the name of the bridge or the dam.

6. See the description of the monitoring network on the CNEMC website: http://www.cnemc.cn/zzjj/jcwl/shjjcwl_699/.

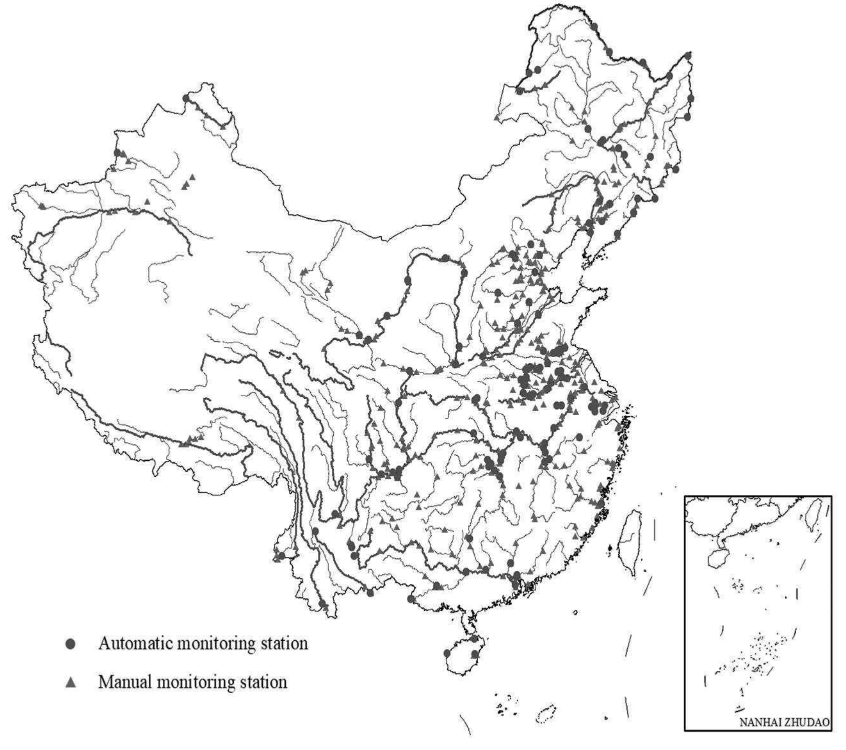

Figure 1. Location distribution of manual and automatic station networks. Color version available as an online enhancement.

There were 100 automatic stations in operation in 2007, 132 in 2012, and 150 in 2015.[7] Again, predetermined exogenous factors, such as river basins' hydrological features, are the key siting determinants of automatic stations.[8] The automatic station network, together with the manual station network, constitutes China's national surface water quality monitoring network. Figure 1 shows the location distribution of the national manual station and automatic station networks in 2012.[9]

7. Figure AI shows the picture of a typical automatic station. The station is built on the bank of Bei river in Zhejiang province.

8. See automatic stations' siting criteria on the CNEMC website: http://www.cnemc.cn/gzdt/wjtz/201203/t20120326_648452.shtml.

9. The locations of automatic stations in the figure are the precise locations of the automatic stations because we know their exact geographical coordinates. Unlike automatic stations, as stated in n. 5, manual stations only report which river section they are monitoring. Hence, the location of the manual stations in the figure represents the centroid of the counties where the river sections that are monitored by the manual stations are located.

Different from manual stations where monitoring activities are conducted once a month (usually in a given day in the first half of each month), automatic stations rely on more advanced technologies with which monitoring activities are conducted every four hours (i.e., 0:00, 4:00, 8:00, 12:00, 16:00, and 20:00). Through the internet and virtual private network technologies, water quality monitoring results gathered by automatic stations are immediately transmitted to the PEMC and CNEMC, and released in real time on MEE's website after 2009. Figure AII (figs. AI–AV are available online) provides a screen shot of the website interface. In contrast, the monitoring results obtained at manual stations are gradually reported from local EPBs to the PEMC, then to CNEMC. Figure 2 illustrates the operation flow charts of the manual station and automatic station networks. The arrows in the figure represent the flow of information on water quality monitoring results. The improved environmental data transparency of monitoring with automatic stations put more environmental regulation pressures on local officials from both the central government and the public.

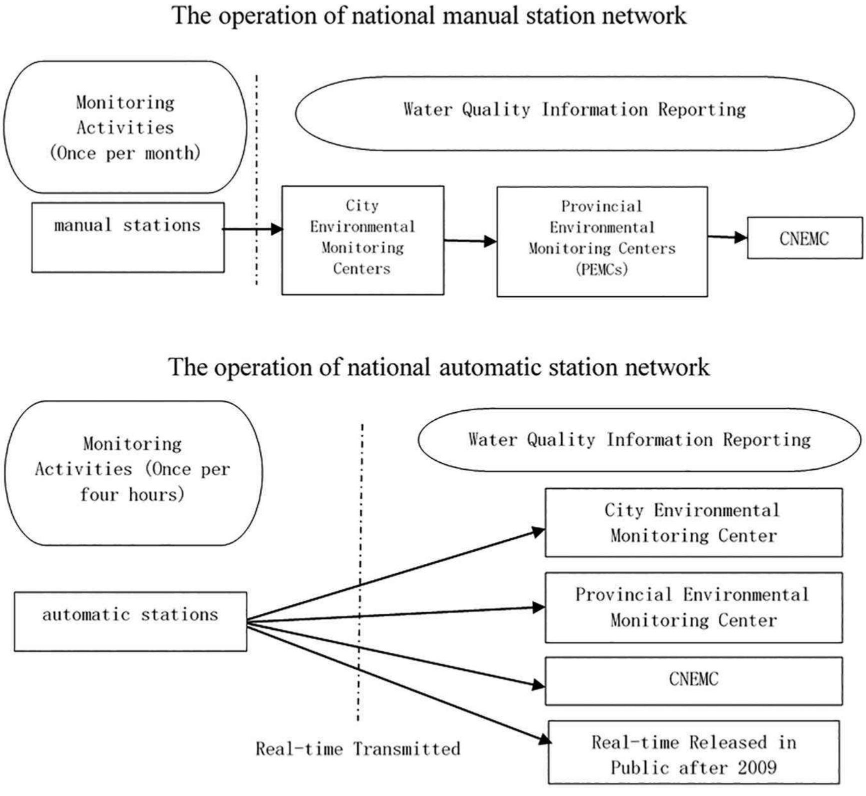

Figure 2. How manual station and automatic station networks operate. CNEMC = China's national environmental monitoring center.

1.3. A Sharp Contrast: Readings from Manual and Automatic Stations

Although formulated at the national level, manual stations' monitoring activities are fully delegated to local EPBs that are primarily local governmental agencies. Given GDP growth as the top priority, local governments would relax top-down regulation pressure and, hence, be more likely to falsify manual stations' water quality monitoring results. In contrast, since the PEMC and CNEMC can access the real-time monitoring readings of automatic stations, there is little room for local governments to play around with the readings.

To illustrate the potential degree of the data manipulation problem, we statistically test whether the readings of manual stations are less than those of automatic stations in the same location. Unlike automatic stations, as discussed in notes 5 and 9, the exact coordinates of manual stations are difficult to pin down. In practice, we choose the sites carefully to ensure that the manual stations and automatic stations under comparison are monitoring the same sites. Specifically, we only choose sites where the manual station's river section name is given by "bridge" or "village," such that we can precisely pin down their locations. In the end, we obtain 37 qualified locations and 231 observations at the local-year level. The *t*-test result presented in panel A of table AIII (tables AI–AIX are available online) further confirms that the difference between average COD concentration readings from automatic and manual stations placed in the same locations are statistically significant.[10] We will provide more evidence about the potential data falsification problem of manual stations in section 3.1.

The high accuracy of water quality monitoring data enables automatic stations to play key roles in cases where real-time water quality information is essential, according to the CNEMC, such as to deliver early warnings for water pollution incidents, secure safe drinking water supplies, and manage water pollution events at administrative boundaries. For instance, during 2007–9, when cyanobacteria bloomed in Lake Taihu, automatic stations gathered a large number of real-time water quality data to secure safe drinking water supplies for local residents. Automatic stations also played a critical role in guaranteeing water supply safety in the Wenchuan earthquake relief and Beijing 2008 Olympic Games.

10. According to the official document of the Ministry of Ecology and Environment of the People's Republic of China, manual stations' readings still affect the evaluation of local officials at locations with automatic stations, but readings of automatic stations have to be simultaneously considered. Consequently, local officials are still incentivized to falsify manual stations' readings when there are automatic stations at the same site. Nonetheless, the degree of manual stations' data falsification tends to be lower in these places because local officials tend to exert more effort in policy enforcement to reduce the readings of automatic stations, which attract public attention and also contribute to their promotion evaluations. Therefore, we claim that the degree of data falsification in sites without automatic stations is more likely to be larger than the difference we quantify here.

2. DATA CONSTRUCTION, AUTOMATIC STATION, AND MANUAL STATION

2.1. Data Sources

We compile multiple data sets to allow for a comprehensive study of the impacts of establishing automatic stations on local pollution controls and public health. The final data set used in our empirical analysis includes information of automatic stations, county level wastewater emissions, and health data for all disease surveillance points (DSPs).

Information on 132 automatic stations[11] is obtained from China's national environmental monitoring center. Unlike manual stations, we know the geographical coordinates and the establishment years of all automatic stations in the data set, which allows us to precisely match their locations to the locations of counties and DSPs. We will show the detailed matching methodology in section 2.2

We obtain 1998–2010 county-level water pollution emissions data from the Chinese Environment Statistics Database (CESD) data set, which records annual firm-level water pollution emissions. We aggregate wastewater emissions from all firms in the data set in each county to calculate the county-level wastewater emissions. We use county-level aggregate emissions instead of firm-level emissions for three reasons. First, as we will show next, the DSP-level health data are essentially recorded at the county level, and we would like to keep the observation units for the pollution analysis and the health analysis at the same level. Second, not all firms are included in the CESD data set. Specifically, a firm is included in the data set if its emissions of any major pollution in the year fall in the top 85% of all firms in the county or the district where it is located. Hence, it is possible that a firm appears in certain years in the data set but is missing in other years. Aggregating emissions to the county level alleviates this data selection problem, and the calculated county-level emissions levels are always 85% of the true emissions levels for all years in the data set. Third, county governments make up the most basic component of the overall structure of the governmental administrative hierarchy in China, and this is so for water pollution regulations as well. For instance, the eleventh five-year plan for water pollution prevention and control in the Huai river basin (2006–10) is implemented at 152 counties in four provinces. Nonetheless, as we will show in section 3.3, our analysis results are also robust to the use of firm-level wastewater emissions data.

The health data are collected from China's disease surveillance point (DSP) system, a mortality-monitoring system comprising reporting points (i.e., counties or urban districts) selected by stratified cluster random sampling. A DSP is usually a county or a district. According to 2005 statistics, the system covers 81 million people, approximately 6% of China's population. The data are available for the years 1991–2000 (covering 142 reporting points) and the years 2004–12 (covering 161 reporting points).

11. This is the total number of automatic stations in 2012. We identify the location and the establishment year of each of the 132 automatic stations.

The data set records the annual number of deaths recorded at each DSP from various causes of death, and the population is accustomed to converting the recorded deaths into mortality rates. We concentrate on mortality rates from digestive diseases, which are mostly related to water pollution (Ebenstein 2012). The age-adjusted mortality rates of digestive diseases during the sample period (1991–2012) are then calculated. The mortality data from all types of diseases and other major nondigestive diseases (e.g., lung cancer, respiratory infections, and cardiovascular diseases) are also collected.

2.2. Merging Data Sets

Since the automatic stations are only able to monitor water pollution from its upstream counties, we need to define counties/DSPs in the treatment group (i.e., those with a downstream automatic station) and in the control group (i.e., those without a downstream automatic station). The geo-coded information of automatic stations and counties/DSPs enables us to accomplish this task.

The basic unit used in analyzing the effect of establishing automatic stations on wastewater emissions is county. To define counties in the treatment and control groups, we first classify automatic stations into two types—interior and boundary automatic stations—according to whether automatic stations are located at city boundaries. Given an interior automatic station, the counties under the jurisdiction of the city where the automatic station is located are sorted into treatment or control groups on the basis of whether the automatic station is located downstream or upstream. Given a boundary automatic station, the counties under the jurisdiction of the automatic station's neighbor cities are accordingly sorted into treatment or control groups based on whether the automatic station is located downstream or upstream.

Figure 3 illustrates how we define counties in the treatment and control groups under the cases of interior and boundary automatic stations. In the diagram on the left, the Yellow River main stream and one of its tributaries flows through the city of Lanzhou, and three counties are under its jurisdiction. The arrows denote the water flow direction; the automatic station (denoted by the triangle) is located in the city interior and in the location where the tributary flows into the main stream. Given the location of this automatic station, we therefore define the county the tributary flows through as the county in the treatment group (gridded) and correspondingly define the other two counties where the automatic station is located upstream as the counties in the control group (in gray). The diagram on the right illustrates the case where automatic stations are located at city boundaries. This automatic station is located on the Huai River in Huaibin county in the city of Xinyang, approaching the boundary with the city of Fuyang. This automatic station is therefore set to monitor the inflow water quality from Xinyang. Hence, we define the counties in Xinyang that the Huai River and its tributaries flow through as the counties in the treatment group (gridded) and define the counties where the automatic station is located upstream and counties where the river and its tributaries do not pass as the counties in the control group (in gray). Following

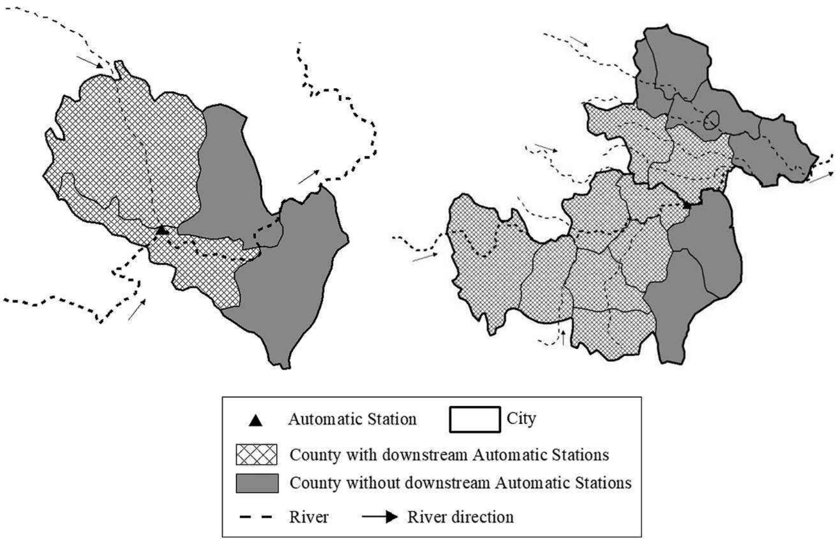

Figure 3. Definition of counties with and without downstream automatic stations

the procedures described above, we define 334 counties as those with a downstream automatic station (treatment group) and 355 counties without a downstream automatic station (control group);[12] thus, the sample contains 689 counties.

The basic unit used in analyzing the health benefit from establishing automatic stations is DSP. Although a DSP is essentially a county, there are only 200 DSPs in China. It is very rare that two DSPs are in the same city. Hence, we slightly modify the method we use to assign counties to treatment and control groups above. However, the spirit is the same: we rely on the direction of river flows and the locations of DSPs relative to automatic stations. In particular, we track for each DSP whether there is an automatic station that lies in any river that passes through the DSP. If the answer is no, then this DSP is sorted as a controlled DSP, otherwise it falls into the treated group.

Figure 4 illustrates how we define the DSPs with and without a downstream automatic station. The diagram on the left shows the DSP counties and the locations of automatic stations in Anhui province. One of the two control DSPs (in gray) does not have a river passing through. The other control DSP is along a river, but there is no downstream automatic station, as indicated by the flow of the river. The automatic station downstream of the treated DSP (gridded) is located in the interior of the province. Similarly, the diagram on the right shows a scenario where automatic stations downstream of

12. Figure AIV plots the kernel density of the percentage of areas that is covered by the dominant watershed in each county in China.

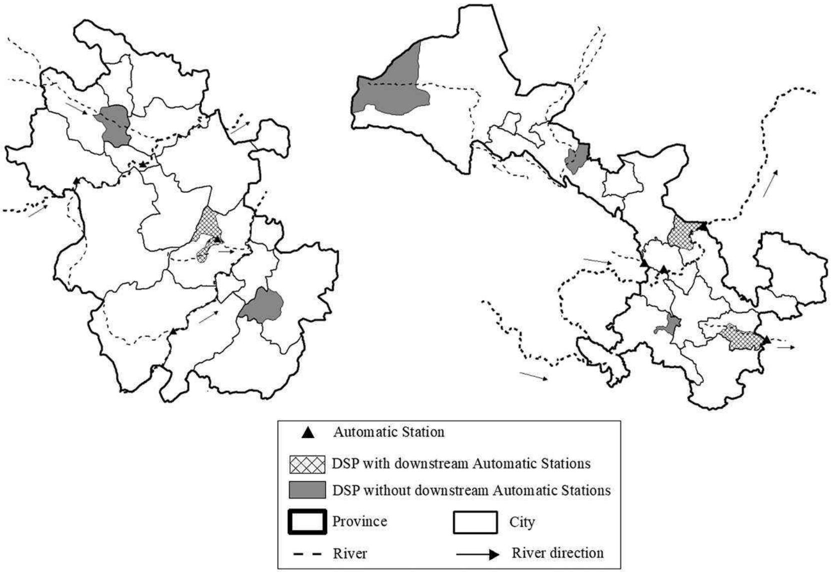

Figure 4. Definition of the disease surveillance points (DSPs) with and without downstream automatic stations.

treated counties are on the province border. Finally, we define 38 DSPs as those with a downstream automatic station (treatment group) and 162 DSPs without a downstream automatic station (control group); thus, the sample contains 200 DSPs.

We further collect data on local development indicators that might affect wastewater emissions and/or mortality from digestive diseases, such as local GDP per capita, the number of hospital beds per thousand population, and municipal piped water coverage. From the China City Statistical Yearbook, we collect city-level GDP per capita, number of hospital beds, and population for 1991–2012. We adjust GDP per capita into real GDP per capita according to the provincial consumer price index (taking 1991 as the base year). The number of hospital beds per thousand population is used as a proxy for development level of the local public health service system. Municipal piped water coverage is collected from the Fifth Nationwide Population Census (2000) statistical data and measured by the percentage of households accessing municipal piped water in each district/county. Data descriptions are presented in table AI.

3. AUTOMATIC STATION ESTABLISHMENT AND WASTEWATER EMISSIONS

3.1. Emissions Reduction Following Automatic Station Establishment

Readings from an automatic station directly capture water pollution emissions from its upstream counties. Therefore, counties with a downstream automatic station face stricter emissions control compared to those without one. In what follows, we identify the effect of establishing downstream automatic stations on wastewater emissions under a difference-in-differences (DID) framework. Specifically, we exploit the variations in automatic station establishment years and the relative locations of counties/districts to the nearby automatic station in the following estimation equation:

$$\log\left(\text{Waste}_{cp,t}\right) = \beta_0 + \beta_1 \text{Auto}_{c,t} + \beta_2 \text{Manual}_{c,t} + \beta_3 \boldsymbol{X}_{c,t} + \delta_c + \gamma_{pt} + \mu_{cp,t}, \qquad (1)$$

where $\text{Waste}_{cp,t}$ is total wastewater emissions from county c located in city p in year t; $\text{Auto}_{c,t}$ is the key independent variable, which equals 1 if there is a downstream automatic station for county c in year t, and 0 otherwise; similarly, $\text{Manual}_{c,t} = 1$ if there is a downstream manual station for county c in year t. The inclusion of $\text{Manual}_{c,t}$ as a control variable in the regression allows us to purge the effect of manual stations out from that of automatic stations and to compare the effects brought by the establishment of automatic and manual stations. Further, $X_{c,t} = \text{gdp}_{c,t-1}$, the lagged GDP per capita, is included as another control variable; δ_c and μ_{cpt} are county fixed effects and an independent and identically distributed (i.i.d.) error term, respectively.[13]

It is possible that the central government is more likely to establish downstream automatic stations earlier for cities with high historical wastewater emissions in order to increase pollution monitoring capability in high-polluting area, which results in a potential selection problem that may bias the estimate of β_1 through reverse causality. Therefore, we include in the regression γ_{pt}, the city-by-year fixed effects, to control for the potential city-level time-varying selection problem. However, it does not rule out the possibility that the locations of automatic stations within a city are endogenous. We address this issue formally in section 3.2 and show that the within-city siting decisions are largely exogenous. Finally, standard errors are clustered at the city level to account for possible correlations in the error terms among counties in the same city.[14]

We add control variables sequentially into the regression, and the regression results are reported in table 1. Column 1 of the table reports the regression results without any control variables. The results indicate that counties with downstream automatic stations emit 21.2% less wastewater compared to those without downstream automatic stations (i.e., either with manual stations or without any monitoring stations). In column 2, the results remain largely unchanged after controlling for lagged county-level GDP. In column 3, we further add the downstream manual station dummy in the

13. If there are multiple automatic stations in a city, our DID strategy would end up comparing upstream and downstream counties for different automatic stations. Adding station-by-year fixed effects can solve this problem. However, since it is rarely the case that one city has multiple stations, our results are robust to the inclusion of these fixed effects. The results with station-by-year fixed effects are not reported but are available upon requests.

14. We also conduct a robustness check with error terms clustered at the province level. The results are robust to alternative clustering units and are reported in col. 1 of table AIX.

Table 1. Effects of Establishing Downstream Automatic Stations on Water Pollutant Emissions

	Log (wastewater) (1)	Log (wastewater) (2)	Log (wastewater) (3)	Log (COD) (4)
Establishment of downstream automatic station	−.212*	−.215*	−.219*	−.242*
	(.127)	(.126)	(.129)	(.137)
Establishment of downstream manual station			.028	.143
			(.171)	(.174)
Other control variables		Yes	Yes	Yes
City-year fixed effects	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes
Number of observations	8,087	8,087	8,087	7,894
Adjusted R^2	.801	.801	.801	.715

Note. This table reports the effect of establishing downstream automatic stations on upstream counties' wastewater emissions. Other controls include log(GDP per capita). Standard errors clustered at city level are reported in parentheses.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

regression as an additional control. While establishing downstream automatic stations still significantly reduces wastewater emissions from upstream counties, the effect of downstream manual stations is small and statistically insignificant. In what follows, we treat column 1 and column 3, that is, specifications without any controls and with a full set of controls, as the baseline regression specifications.

The sharp contrast between the effects of automatic and manual stations is somewhat surprising but reasonable given the discussions earlier in section 1. Water quality readings of manual stations are reported by local officials to the central government and the public. Although the central government is determined to control pollution, local officials are incentivized to falsify manual stations' water quality monitoring results given that both local GDP growth and environmental quality are key determinants of their promotions. Such a principle-agent problem is largely alleviated by setting up automatic stations, the readings of which are reported to the central government directly through advanced information technologies. This leaves local officials with little space for data manipulation. Indeed, as shown in panel A of table AIII and figure AIII, readings from manual stations are much smaller than those from nearby automatic stations. With automatic monitoring, the only way to meet local environmental targets set by the central government is to honestly enforce pollution regulation, and the pollution-reduction effect becomes more pronounced.[15] Therefore, improving monitoring technologies proves to be effective in promoting local governments' environmental performance, especially in developing countries where local officials have a strong incentive to sacrifice environmental quality for economic growth.

Alternatively, one can also adopt the spatial regression discontinuity (RD) framework to identify the effect of establishing automatic stations on wastewater emissions. For example, He et al. (2020) show that firms in the immediate upstream of a manual station emit less water pollution than firms in the immediate downstream of the station. We adopt the DID framework instead of the RD framework in our analysis mainly because the DID framework allows us to identify the global effects of establishing downstream automatic stations on all upstream firms near the stations, while the RD framework only captures the local effect on firms in the immediate upstream.

Indeed, water pollution regulations do not only affect firms in the immediate upstream of a monitoring station, although the regulation toughness may differ across firms by their distances to the station. Figure 5 illustrates the locations of firms that are required to implement water pollution clean-up projects set by the five-year plan for water pollution prevention and control in one example city. As shown in the figure, there are 10 counties in the city with a downstream automatic station. Among the 10 counties, six are treated counties and the rest belong to the control. During each five-year plan, city-level emissions abatement targets are first decomposed to counties in the city, and counties then decompose their designated abatement targets to all firms in its jurisdiction. In the figure, we also label the locations of major water polluting firms that are required to abate emissions as scheduled by the eleventh five-year plan (2006–10) for water pollution prevention and control.[16] The figure indicates that these regulated water-polluting firms are all located at the treated counties we define earlier, and they are not only located at the automatic station's near-upstream area (at the same county as the automatic station locates) but also further-upstream (located at the upstream counties). Such observations provide support for the global effects of establishing downstream automatic stations that can only be captured by adopting the DID framework. As He et al. (2020) are interested in the impact on firm behavior, an RD approach is still appropriate. In contrast, the ultimate goal of our study is to quantify the effect of establishing downstream automatic stations on public health, which is

15. There is wide heterogeneity in local officials' promotion incentives in China. Prefecture-level officials above 56 years old are unlikely to be further promoted along the bureaucratic ladder (He et al. 2020). Table AII shows that the effect of establishing a downstream automatic station is statistically insignificant and less pronounced in regions where the city secretary party's age is above 56 years old.

16. Note that firms that show up in the figure are the "key" firms that are required to take emissions abatement action. Such firms are typically major polluters in the city. The name list of the "key" firms is provided by the local government.

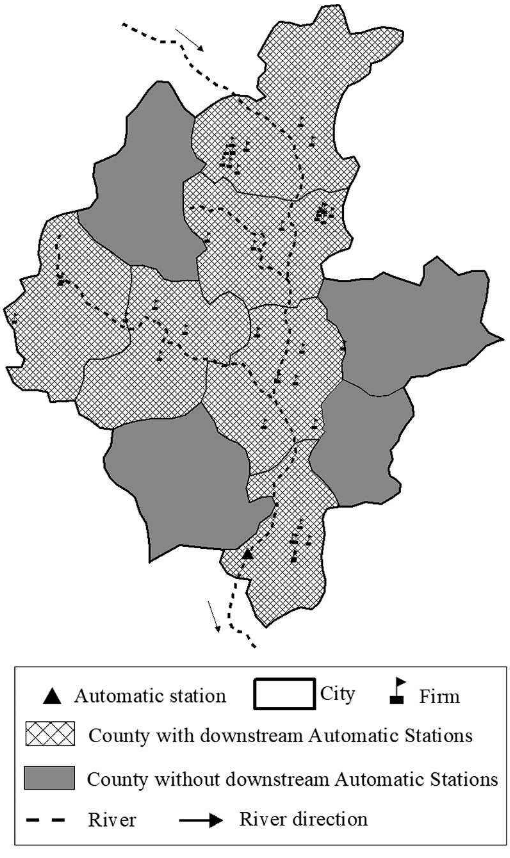

Figure 5. Water-polluting firms required to implement clean-up projects in an example city

affected by the pollution reduction behavior of all the upstream firms near the stations, not only those in the immediate upstream of the station; hence, a DID approach is more appropriate.

The reduction in wastewater emissions would have led to an improvement in water quality. To directly test this hypothesis, one may examine whether water quality readings from an automatic station changed before and after another automatic station is newly established in its upstream. The new automatic station incentivizes its upstream counties to reduce wastewater emissions, which also improves the reading from the incumbent automatic station that is in the downstream of the new station. In the data set, there are only a few automatic stations in the upstream of which an automatic station was newly established during the sampling period. In the end, we identify 30 out of 132 automatic stations that satisfy the requirement. Due to the limited sample size, we do not conduct a regression-based test of the hypothesis. Instead, we calculate the average COD concentration readings from these stations before and after a new upstream station was established and perform a *t*-test on their difference. As expected, the result of the *t*-test reported in panel B of table AIII indicates an improvement in water quality following the establishment of an upstream automatic station. Alternatively, one can test whether water quality readings from an incumbent automatic station changed before and after another automatic station is newly established in its downstream. Consistent with our main story, establishing a downstream automatic station will directly contribute to water quality reading improvement of the incumbent upstream station. The *t*-test result reported in panel C of table AIII again confirms our hypothesis.

3.2. Identification Validity Tests

3.2.1. Potential County-Level Selection Problems

As discussed in section 3.1, the city-by year fixed effect γ_{pt} in equation (1) controls for potential city-level time-varying selection problems. However, it is unable to control for the possibility that the station siting decisions within a city are endogenous: downstream automatic stations may be established earlier in counties with higher GDP or higher historical emissions levels within a city. Conversely, city leaders facing pollution reduction mandates may be able to influence the automatic station siting decision; therefore, they may strategically place the automatic station in the downstream of a relatively less polluted county to make the city "appear to be clean." If such selections happen, the estimated β_1 will still be biased.[17] In what follows, we provide several diagnostics for this potential problem.

First, as discussed in section 1.2, the siting of water quality monitoring stations largely depends on river basins' hydrological features, which city leaders have little control over. Using within-city variations in the timing of automatic station setup, we formally show that the timing and siting choices of automatic stations are uncorrelated with past local economic and environmental quality conditions. Specifically, for each county in our sample, we create a dummy that equals to 0 if there is no automatic station in its downstream in a particular year and equals to 1 if an automatic station is just established in this year. Since we study the timing of establishing downstream

17. Less polluted counties can be systematically different from more polluted counterparts in some aspects (selection variables). If the effects of the unobserved selection variables are time invariant, then the DID setting could solve the selection problem by differencing this effect out. Econometrically, the effect of this selection problem is already controlled by the county fixed effects δ_c in eq. (1). If, on the other hand, the effects of the selection variables are time varying, then their effects could not be fully differenced out by the DID estimator. Say, for example, a common demand shock hit firms in a city and increases firms' emissions, but the effect is in general larger for firms in polluting industries that are unevenly distributed across counties in the city. If this event also pushes the central government to establish automatic stations in the downstream of counties that are most heavily affected by the shock, then $\text{Auto}_{c,t}$ can be correlated with the error term $\mu_{cp,t}$ in eq. (1).

automatic stations, we drop all county-year combinations where downstream automatic stations for the county have already been established in the previous years. We then regress this dummy variable on a series of county- and city-level variables such as lagged water pollution emissions, lagged GDP, and lagged population. We experiment with different fixed effects combinations, such as year fixed effects, county fixed effects, station fixed effects, and city-by-year fixed effects. We also experiment with different clustering levels (i.e., county vs. city). The estimation results are reported in table AIV, which reassures the exogeneity of automatic station siting decisions and provides further support for the validity of the DID identification strategy.

Second, another way to partially control for the effect of time-varying county-level selection problems is to include county-by-year linear trends in the regression. The estimation results are pretty close to the main results reported in column 2 of table 1.[18]

Finally, the finding that automatic station siting is uncorrelated with counties' economic and environmental conditions and that the DID results are robust to the inclusion of county-specific linear trends implies that there should be no systematic difference in the preexisting wastewater emissions trends between the treated and control groups. This is the key identification requirement (i.e., the "common trend" assumption) for the DID analysis to be valid. To formally test this assumption, we examine the yearly dynamic effects of establishing downstream automatic station on wastewater emissions with the following event-study regression:

$$\log\left(\text{Waste}_{cp,t}\right) = \alpha + \sum_{\tau=-4}^{9+} \beta_\tau \text{Auto}_{c,t+\tau} + \theta \text{Manual}_{c,t} + \rho X_{c,t} + \delta_c + \gamma_{pt} + \mu_{cp,t}, \qquad (2)$$

where $\text{Auto}_{c,t+\tau} = 1$ if a downstream automatic station is established τ years prior to ($\tau \geq 0$), or τ years after ($\tau < 0$), year t in county c. We choose $\tau = -5$, five or more years before the establishment of downstream automatic stations, as the base year for the event study.

The parameters of interest are β_τ's, representing changes in wastewater emissions from counties in the treatment group (counties with a downstream automatic station) compared to the base year, relative to that in the control group. The estimated β_τ's, together with their 95% confidence intervals, are plotted in figure 6. The estimated β_τ for $\tau < 0$ are all statistically insignificant and close to zero, indicating that there

18. See col. 4 of table AIX. Directly adding unit-specific time linear trends for the entire sample period in a DID setting may absorb considerable treatment effect (Bhuller et al. 2013). This is especially true when the treatment effect increases (decreases) with time approximately linearly, which is the case in our application (see fig. 6). Therefore, following Bhuller et al. (2013), we estimate county-year linear time trends in wastewater emissions in sample years before the establishment of automatic stations. The estimated linear trends are then added as a control variable for the entire sample period. Due to the two-step nature of the procedure, standard errors are bootstrapped.

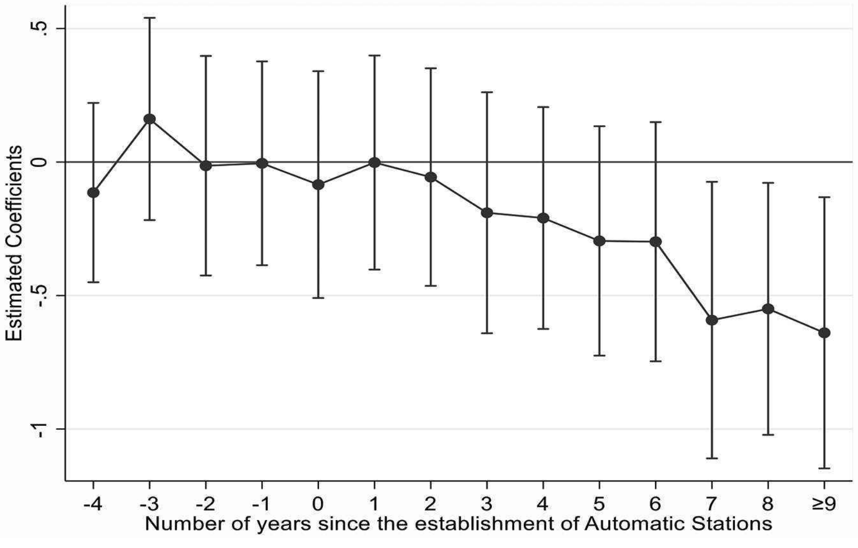

Figure 6. Dynamic effects of establishing automatic stations on wastewater emissions. The figure plots the results of the wastewater emissions event study regression corresponding to equation (2). Standard errors are clustered at the city level. The horizontal axis measures the number of years since the establishment of automatic stations. The plots connected by the solid line indicate changes in wastewater emissions compared to five or more years before the establishment of automatic stations conditional on city-by-year fixed effects, county fixed effects, the establishment of manual stations, and lagged log(GDP per capita). Color version available as an online enhancement.

are no preexisting differences in the trend of the dependent variable between the treated and control groups, and the parallel trend assumption holds.

3.2.2. Potential Spillover Effects

Although the "parallel trends" assumption holds prior to station establishment, it is still possible that polluting industries in the treated counties may slow down their expansion or even move to the control counties after a downstream automatic station is established.[19] If such spillover effect presents, our estimated treatment effect on emission reduction would be overstated, that is, be more negative than the real change in total emissions. One way to get a sense of how large this spillover effect might be is to

19. It is also possible that a firm in the upstream county of an automatic station may migrate to locations in the same county but farther away from the station. This "within-county migration" effect can still be captured by our DID strategy, but it cannot be captured by a spatial RD design discussed earlier in sec. 3.1 since the firm already migrated out from the distance bin around the station.

aggregate emission information at higher administrative levels. It is reasonable to assume that cross-city spillovers are less likely to happen than cross-county spillovers. If the estimated treatment effects obtained from using county-level data and city-level data are similar with each other, spillover effect would not be a serious concern.

Therefore, we aggregate emissions to city-level, identify upstream and downstream cities, and reestimate equation (1) except that we drop the city-by-year fixed effects and replace the county fixed effects by city fixed effects. The estimation results from this new regression are reported in table AV. For ease of comparison, we also replicate the results obtained from estimating equation (1) using the county-level data in the same table. Perhaps not surprisingly, the magnitude of the estimated treatment effect declines when we use city-level data for the regression. However, the magnitude of the decline is only moderate, from −0.219 to −0.172. Therefore, even though the spillover effect described above may exist, its magnitude is modest, and it does not seriously affect the sign of our estimated treatment effect at the very least.

3.3. Robustness Checks

In this section, we conduct a few robustness checks to ensure that the results above are not driven by model specifications and concurrent shocks. First, we conduct a "falsified timing test." Specifically, we randomly draw a station establishment year for each automatic station, estimate the DID model with the falsified establishment year, and obtain the estimated DID coefficient. We repeat this exercise 500 times. Given this random treatment status generation process, a necessary condition for our model to be correctly specified is that these "falsified" DID coefficients should be centered around zero. The kernel density function of the estimated falsified DID coefficients is plotted in the left panel of figure AV. As expected, the distribution of the coefficients is narrowly centered around zero, and the true treatment effect reported in table 1 is much greater than two standard deviations away from the mean of the empirical distribution of the falsified coefficients. Therefore, the estimated treatment effect in table 1 is unlikely to be obtained by chance from a distribution of sample estimates with the underlying population-level treatment effect being zero.

Second, the establishment of automatic stations should only strengthen the monitoring of water pollution emissions. As a placebo test, we test the impact of establishing automatic stations on air pollution emissions from their upstream counties. Table 2 reports the results where waste gas emissions, dust emissions, and SO_2. emissions are used as dependent variables in equation (1). The null results of the placebo tests in table 2 further confirm that the reduction in upstream counties' water pollution emissions is brought by establishing downstream automatic stations but not by some other coinciding policies or shocks that may simultaneously reduce water and air pollution emissions.

Third, in our main analysis model (1), we use wastewater emissions to approximate the emissions of many water pollutants that may harm human health. Alternatively, we reestimate equation (1) using COD emissions, a key pollutant under regulation

Table 2. Placebo Tests: Effects of Automatic Stations on Air Pollutant Emissions

	Log (waste gas) (1)	Log (dust) (2)	Log (SO_2) (3)
Establishment of downstream automatic station	.032	−.015	−.123
	(.099)	(.104)	(.094)
Control variables	Yes	Yes	Yes
City-year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Number of observations	8,127	8,094	8,128
Adjusted R^2	.831	.696	.787

Note. This table reports the results of the robustness checks about effect of establishing automatic stations on upstream counties' air pollution emissions. Controls include a dummy variable indicating the establishment of downstream manual station and log(GDP per capita). Standard errors clustered at city level are reported in parentheses.

during the sampling period, as the dependent variable.[20] The estimation results are reported in column 4 of table 1. Reassuringly, the establishment of automatic stations, rather than that of manual stations, significantly reduced upstream counties' COD emissions, which is consistent with the main results in table 1 where wastewater emission is used as the dependent variable.

Fourth, as stated in section 2.1, we use county-level data, rather than firm-level data, to analyze the effects of automatic stations on wastewater emissions. The main reason is to keep the observation units for the wastewater and public health analyses (the health analysis results are reported in sec. 4) at the same level, and to avoid the potential sample selection problem when using the firm-level data. Nonetheless, we perform another robustness check by conducting a firm-level DID regression. Specifically, firms in the treated counties are assigned as firms in the treatment group, and firms in the controlled counties are those in the control group. The estimation results from this firm-level DID regression, reported in table AVII, also confirms that the establishment of automatic stations effectively reduces water pollution emissions from upstream counties.

20. Ebenstein (2012) found a significant relationship between digestive diseases and water grade in China, and COD is the major pollutant used to calculate water grade in the country (see Ministry of Environmental Protection of the People's Republic of China 2002). Although COD has been shown to be positively correlated with digestive disease (Lin et al. 2000), it does not necessarily mean that all the health benefits of water quality improvement are attributed to the reduction in COD emission. Nonetheless, many health-related pollutants in wastewater, such as nitrate and various organic matters, are in fact positively correlated with COD (Morales-Suarez-Varela et al. 1995; Sandor et al. 2001; Gulis et al. 2002; Zaghloul et al. 2019). Besides, unlike other pollutants, COD emission is heavily monitored in China and its information is readily available, which is the main reason that we only conduct a COD analysis here.

Fifth, we check the sensitivity of our results by adopting an alternative set of sampled counties and an alternative definition of treatment and control groups. Specifically, all the counties within 100 km from the automatic stations are taken as the sampled counties. Prior to the establishment of an automatic station, all the counties within 100 km from it are untreated. After the automatic station is established, counties that are located in its upstream and within 100 km from the automatic station are treated, while those that are located in its downstream and within 100 km from the automatic station are untreated. Columns 1 and 2 in table AVIII report the estimation results from this alternative DID analysis. The estimated coefficients are similar to the main analysis results shown in section 3.2 above.

Finally, the average treatment effect reported in table 1 is obtained by comparing the average wastewater emissions of counties with and without a downstream automatic station in each year. A more appropriate estimate of the average treatment effect, as pointed out by Callaway and Sant'Anna (2021), is the weighted average of the average treatment effects for different treatment groups, that is, counties that switched to different treatment status in different years.[21] The average treatment effects on wastewater emissions obtained by applying the extended difference-in-differences estimator proposed by Callaway and Sant'Anna (2021), with and without including control variables, are reported in column 7 of table AIX. Again, the estimation results are similar to the main results in table 1, which strengthens the validity of our identification strategy.

4. AUTOMATIC STATION ESTABLISHMENT AND PUBLIC HEALTH

We have shown that the establishment of downstream automatic stations significantly reduces wastewater emissions from the upstream counties. Such reduction in wastewater emissions might have positively affected the health conditions of local residents. In this section, we focus on quantifying this potential health improvement from establishing automatic stations.

4.1. The Substantial Health Benefit

We use the following DID estimation strategy to identify the effect of establishing automatic stations on upstream counties' public health condition.

$$\text{Deathrate}_{k,t} = \beta_0 + \beta_1\text{Auto}_{k,t} + \beta_2\text{Manual}_{k,t} + \boldsymbol{\beta_3 X_{k,t}} + \zeta_t + \eta_k + \varepsilon_{\text{k,t}}, \quad (3)$$

where $\text{Deathrate}_{k,t}$ represents the death rates from digestive diseases, diseases that are shown to be sensitive to drinking water quality in China (Ebenstein 2012), in DSP

21. Callaway and Sant'Anna (2021) point out that it is more appropriate to focus on the average treatment effect across treatment groups instead of the average treatment effect for each group when the number of treatment groups is relatively large.

point k in year t; the key independent variables $\text{Auto}_{k,t}$ and $\text{Manual}_{k,t}$ are defined similarly as in equation (1); $X_{k,t} = \{\text{gdp}_{k,t-1}, \text{bed}_{k,t-1}\}$ is a vector of control variables that may affect mortality from digestive diseases, where $\text{bed}_{k,t-1}$ is the lagged number of hospital beds per thousand population; ζ_t, η_k, and $\varepsilon_{k,t}$ are year fixed effects, DSP fixed effects, and the i.i.d. error term, respectively. The interpretations of β_1 and β_2 are similar to those in equation (1).[22] Again, standard errors are clustered at the city level to account for possible correlations in the error terms among counties in the same city.[23]

Table 3 presents the estimation results of equation (3). The results in the first two columns of the table are in accordance with including (or not) downstream manual station dummy and other control variables in the estimation. With these results, we examine the change of digestive disease death rates due to the establishment of downstream automatic stations. We find that the coefficients estimated on the establishment of automatic stations in both columns are negative and statistically significant at the 5% level, meaning that health conditions for residents in counties with a downstream automatic station significantly improve.

In particular, the death rate from digestive diseases for DSPs with downstream automatic stations drops by around 2.3 persons per 10,000 population compared to those without downstream automatic stations. Given that the average death rate of digestive disease is 9.28 persons per 10,000 population, our results imply that a 22% reduction in wastewater emissions leads to a 24% reduction in the death rate. We will show later in section 4.2 that such health benefit is mainly driven by a 46% reduction in the emissions of wastewater with high pollutant concentration.

The decline in death rate in our context is comparable to Ebenstein (2012), who estimates that a one-grade degradation of water quality raises the digestive cancer death rate by 9.7%.[24] The magnitude should be greater if the deaths from noncancer

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22. Unlike in eq. (1), we do not control for city-by-year fixed effects in eq. (3) because there is only one DSP for most cities. Therefore, the city-by-year fixed effects would absorb almost all variations that can be used to identify β_1 and β_2.

23. We also conduct a robustness check with error terms clustered at the province level. The results are robust to alternative clustering units and are reported in cols. 2–3 of table AIX.

24. According to the Environmental Quality Standard for Surface Water (Ministry of Environmental Protection of the People's Republic of China 2002), COD concentration declines by around 16% for a single-grade improvement of water quality. The 24% decline in COD emissions, shown in table I, corresponds to a roughly 1.6 grade-point increase in water quality, implying that our estimated death rate reduction from one-grade improvement in water quality is $24\,\%/1.6 = 15\,\%$, which is in the same order of magnitude as the coefficient estimated in Ebenstein (2012). Indeed, the average planned increase in water quality grade during 2000–2010 for water body sections monitored by automatic stations is 1.83 (Water Pollution Prevention and Control Plan during the tenth and eleventh five-year plans), which, combined with the estimate from Ebenstein (2012), implies an 18% reduction in the digestive disease death rate. This is also in the same order of magnitude as our estimated treatment effect from establishing downstream automatic stations (i.e., 24% reduction in the digestive disease death rate).

Table 3. Effects of Establishing Automatic Stations on Digestive Diseases Death Rate and Life Expectancy at Birth

	Digestive Disease Death Rate		Life Expectancy at Birth	
	(1)	(2)	(3)	(4)
Establishment of downstream automatic station	−2.387***	−2.257**	2.807***	3.135***
	(.898)	(.868)	(.721)	(.794)
Establishment of downstream manual station		−1.021		−.884
		(.924)		(.885)
Other control variables		Yes		Yes
Year fixed effects	Yes	Yes	Yes	Yes
DSP fixed effects	Yes	Yes	Yes	Yes
Number of observations	2,743	2,743	2,688	2,688
Adjusted R^2	.560	.566	.482	.484

Note. This table reports the estimated effect of the establishment of downstream automatic stations on digestive disease death rate. Digestive disease death rate is age-adjusted by calculating age-specific death rates and creating weighted averages using the population structure in China's 2010 census. Control variables include log(GDP per capita) and log(hospital beds per 1,000 residents). Standard errors clustered at the city level are reported in parentheses.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

digestive diseases are involved. Our result therefore could roughly correspond to the benefit of about a two-grade improvement of water quality. Our finding is also comparable to the benefit of air pollution reduction documented by many studies in the literature. For example, Tanaka (2015) finds that the "Two Control Zones" policy in China that mainly aims to reduce SO_2 emissions reduced infant mortality by 20% in the treated cities. Similarly, Fan et al. (2020) find that the winter heating system in China decreased air quality by 36%, which led to a 14% increase in the mortality rate. The health benefit in our context is brought by a strengthening of water pollution regulation enforcement due to enhanced monitoring, while that in the two studies above is brought by new environmental policies or pollution-creating practices. Hence, our results demonstrate the necessity of environmental regulation enforcement, in addition to environmental policy itself, especially in developing countries characterized by weak enforcement.

Column 2 further indicates that manual stations alone have insignificant health benefits. The results are in line with our findings in section 3.1 that manual stations do not significantly reduce wastewater emissions from the upstream counties, while automatic stations do a much better job in terms of wastewater emissions control.

Death rate reduction from digestive diseases due to the establishment of downstream automatic stations significantly increases the life expectancy at birth for local residents.[25] Relative to digestive disease death rates, life expectancy at birth is a more comprehensive measurement of the death risk because it is generated from all the types of disease death rates. In particular, the last two columns of table 3 show that establishing downstream automatic stations increases the life expectancy at birth in their upstream areas by 2.81 years (col. 1) and by 3.14 years if the downstream manual station dummy and other control variables are included in the regression (col. 2).

4.2. Identification Validity and Connection with Wastewater Emissions' Treatment Effect

As in the previous section, a natural question that may arise is whether the siting choice of the automatic stations is exogenous to historical DSP-level health conditions. We formally test this potential selection problem in table AVI, following the similar estimation procedures described in section 3.2. In column 1 of table AVI, only historical DSP-level health conditions are used to predict whether a downstream automatic station is established for a DSP in the future; we then add historical DSP-level emissions records and economic conditions as additional predictors in column 2. The results in both columns fail to reject the null hypothesis that the siting choice of automatic stations is exogenous to historical DSP-level conditions.

We then formally test whether the common trend hypothesis holds by analyzing the yearly dynamic effects of establishing downstream automatic stations on the digestive disease death rate and the life expectancy at birth. The results are shown, respectively, in figure 7 and figure 8, which plot the estimated coefficients of the yearly automatic station dummies as well as the 95% level confidence intervals. These coefficients are again interpreted as the changes in the digestive disease death rate and the life expectancy at birth in the DSPs with downstream automatic stations compared to the base year (i.e., six or more years before the establishment of automatic station), relative to those in the DSPs without downstream automatic stations.

We first observe that the changes in digestive disease death rate and life expectancy at birth in the areas with downstream automatic stations do not significantly differ from the corresponding levels in the areas without downstream automatic stations (the zero benchmark) at the 95% confidence level before the establishment of automatic stations.

25. Life expectancy at birth is calculated from static life tables developed from all types of disease death rates of each age group. The average life expectancy at birth as calculated is 78.52 years, which is 3–4 years greater than the statistics reported by Chen et al. (2013), where the same data set is adopted. The reason is that we do not consider nondisease death rates (i.e., injures, accidents) in generating life tables.

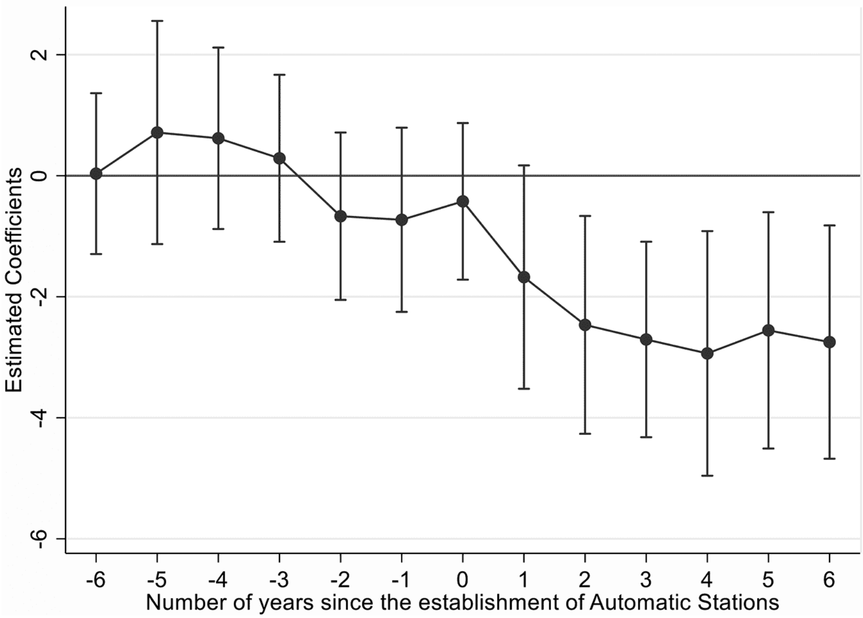

Figure 7. Dynamic effects of establishing automatic stations on digestive disease death rate. The figure plots the results of the digestive disease death rate event study regression. Standard errors are clustered at the city level. The horizontal axis measures the number of years since the establishment of automatic stations. The plots connected by the solid line indicate changes in the digestive disease death rate compared to seven or more years before the establishment of automatic stations conditional on year fixed effects, disease surveillance point (DSP) fixed effects, the establishment of manual stations, lagged log(GDP per capita), and lagged log(hospital beds per 1,000 residents). Color version available as an online enhancement.

Therefore, the parallel trend assumption holds, which ensures the validity of the DID identification strategy.[26]

Second, digestive disease death rate (life expectancy at birth) starts to decline (increase) from the first year after the establishment of downstream automatic stations. However, shown by figure 6, wastewater emissions start to decline from the second year following station establishment. This comparison seems counterintuitive at first glance because at the very least, the health effect should appear no earlier than the emissions reduction effect of establishing automatic stations. However, we argue that

26. Unsurprisingly, similar to the exercise conducted in sec. 3.2, the DID results obtained by additionally controlling for county-by-year trends in death rates and life expectancy, reported in cols. 5 and 6 in table AIX, are in line with the main results reported in table 3.

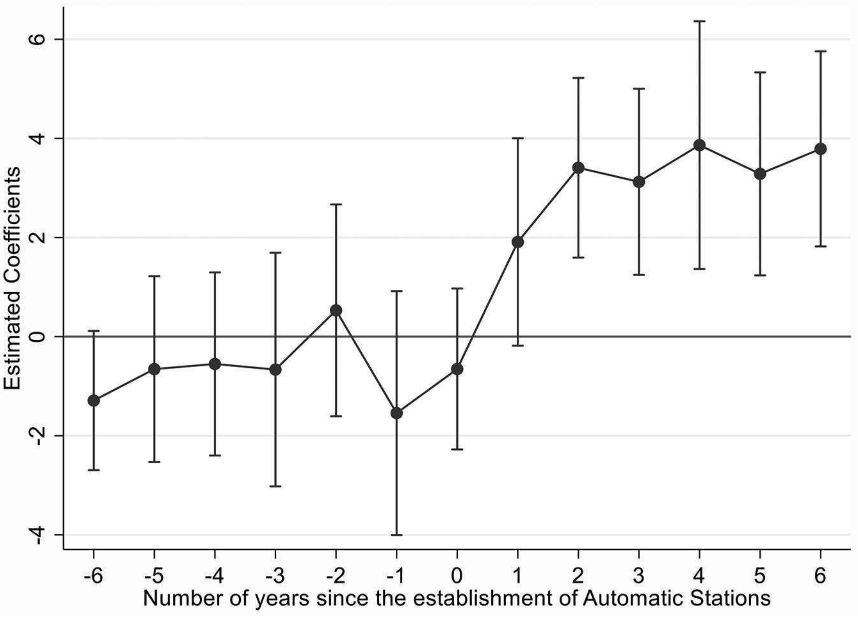

Figure 8. Dynamic effects of establishing automatic stations on life expectancy at birth. The figure plots the results of the life expectancy event study regressions. Standard errors are clustered at the city level. The horizontal axis measures the number of years since the establishment of automatic stations. The plots connected by the solid line indicate changes in life expectancy at birth compared to seven or more years before the establishment of automatic stations conditional on year fixed effects, disease surveillance point (DSP) fixed effects, the establishment of manual stations, lagged log(GDP per capita), and lagged log(hospital beds per 1,000 residents). Color version available as an online enhancement.

total wastewater emission is an imperfect measure of health-related emissions. It might be the case that the volume of wastewater is large, but the concentration of health-damaging pollutants such as COD and NH3-N in the mass of wastewater is low. A more appropriate measure is the emissions of wastewater with different levels of pollutant concentration (i.e., pollutant emissions/wastewater emissions). In particular, we divide wastewater emissions into three categories: those with high, medium, and low COD concentrations. Specifically, for each county, we find the pre–station establishment terciles of firm-level wastewater COD concentration. Denote these two terciles by $\Gamma_{c,1}$ and $\Gamma_{c,2}$, with $\Gamma_{c,1} > \Gamma_{c,2}$. If a firm's wastewater COD concentration is above $\Gamma_{c,1}$ (below $\Gamma_{c,2}$) in a given year, it is categorized as a high- (low-) concentration firm in that year. If its COD concentration is between $\Gamma_{c,1}$ and $\Gamma_{c,2}$, then it is categorized as a medium-concentration firm. The summation of wastewater emissions from high-/medium-/low-concentration firms in each county in each year is defined as the emissions of wastewater with high/medium/low COD concentration at county-year level.

The DID estimation results reported in table 4 indicate that high-concentration wastewater emissions significantly decrease following the establishment of automatic stations, but the effects on medium- and low-concentration wastewater emissions are statistically insignificant. Hence, local officials mainly tightened the environmental enforcement on high-concentration firms as a response of the improvement in monitoring technology.

Compared with wastewater emissions with medium or low pollutant concentrations, those with high pollutant concentration are more responsible for human health deterioration. As shown in the upper panel of figure 9, high COD concentration wastewater emissions start to decline immediately following the establishment of automatic stations, which now happens earlier than the decline in the digestive disease death rate. The insignificant decline in total wastewater in the first several years after automatic station establishment shown in figure 6 is mainly due to the slight increase in medium-/low-concentration wastewater emissions during those years (see figure 9*B*). This is also reasonable since the initially high-concentration polluters reduce pollution

Table 4. Effects on Wastewater Emissions: By COD Concentration in Wastewater

COD Concentration in Wastewater	High (1)	Medium (2)	Low (3)
Establishment of downstream automatic station	−.456**	.039	.014
	(.174)	(.170)	(.240)
Control variables	Yes	Yes	Yes
City-year fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Number of observations	6,504	5,797	4,066
Adjusted R^2	.649	.586	.590

Note. This table reports the effect of establishing downstream automatic stations on upstream counties' wastewater emissions by COD concentration in wastewater. Controls include a dummy variable indicating the establishment of downstream manual station and log(GDP per capita). We separate wastewater into three categories, that with high/medium/low COD concentrations. Specifically, for each county, we find the pre–station establishment terciles of firm-level wastewater COD concentration. Denote these two terciles by $\Gamma_{c,1}$ and $\Gamma_{c,2}$, with $\Gamma_{c,1} > \Gamma_{c,2}$. If a firm's wastewater COD concentration is above $\Gamma_{c,1}$ (below $\Gamma_{c,1}$) in a given year, it is categorized as a high- (low-) concentration firm in that year. If its COD concentration is between $\Gamma_{c,1}$ and $\Gamma_{c,2}$, then it is categorized as a medium-concentration firm. The summation of wastewater emissions from high-/medium-/low-concentration firms in each county in each year is defined as the emissions of wastewater with high/medium/low COD concentration at county-year level. Standard errors clustered at city level are reported in parentheses.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

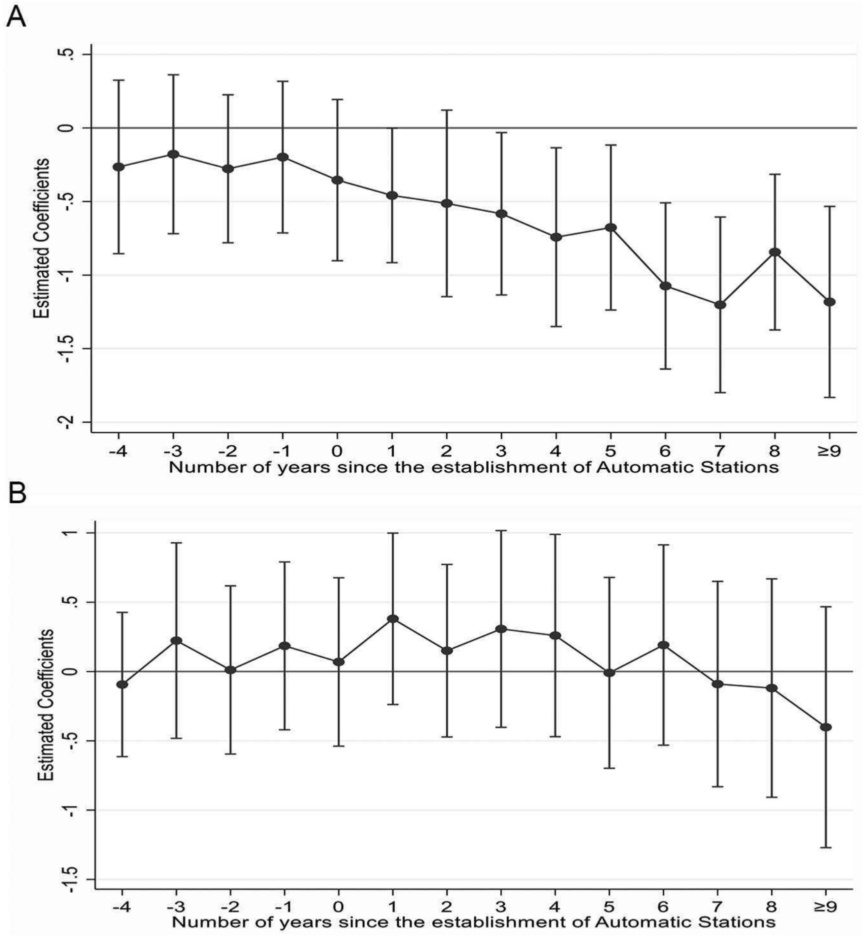

Figure 9. Dynamic effects of establishing automatic stations on emissions of wastewater with high (*A*) and medium/low (*B*) COD concentrations. The figure plots the results of the event study regressions where the dependent variables are wastewater emissions with high (*A*) and medium/low (*B*) COD concentration. Standard errors are clustered at the city level. The horizontal axis measures the number of years since the establishment of automatic stations. The plots connected by the solid line indicate changes in wastewater emissions with high (*A*) and medium/low (*B*) COD concentrations compared to five or more years before the establishment of automatic stations conditional on city-by-year fixed effects, county fixed effects, the establishment of manual stations, and lagged log(GDP per capita). Color version available as an online enhancement.

intensity and become medium-/low-concentration polluters following the stricter environmental policy enforcement.[27]

Another possible concern about the DID identification above comes from the nature of water flow and how water pollution affects health. Of course, water pollution emissions in a DSP decrease, and the health condition of residents in this county improves, if this county has a downstream automatic station. This effect is what we intend to capture by β_1 in equation (3). However, health conditions in a county could also be improved if it has an upstream automatic station, because counties in the upstream of this automatic station will reduce water pollution emissions, which also benefits residents in this downstream DSP. Fortunately, only 6.4% DSPs have upstream automatic stations; hence, it is unlikely for the estimated β_1 to be contaminated by the possibility that some DSPs have an upstream automatic station. To further alleviate this concern, we conduct a complementary analysis by adding an indicator that equals 1 for DSPs with upstream automatic stations in a given year. The estimation results are reported in table 5. The estimated coefficients of the downstream automatic station dummies are statistically significant and are similar to the results in table 3, which strengthens the validity of the identification strategy in equation (3). Besides, the coefficients estimated on the upstream automatic station dummies are smaller and statistically insignificant. The estimation results provide evidence for the health effects of establishing downstream automatic stations rather than establishing upstream automatic stations.

As a placebo test, we examine whether the death rate from accidents is also affected. Apparently, establishing automatic stations has little effect on drivers of accidents, such as traffic conditions and crime rate. As expected, estimation results reported in the first two columns of table 6 indicate that the accident death rate is rarely affected, which lends additional support to the validity of the DID identification.

In the main estimation, we quantify the decline in the digestive disease death rate because the relationship between digestive disease and water quality has been established in the literature (Ebenstein 2012). However, it might be possible that death rates of other diseases can also be affected, either directly or indirectly through the occurrence of complications. Therefore, we test whether automatic station establishment also affects death rates from respiratory and cardiovascular diseases, which, together with digestive diseases, account for 75% of all disease-related death.[28] As shown by columns 3–8 of table 6, death rates of neither diseases are affected. Possibly, respiratory and cardiovascular diseases are overall mainly affected by air quality (Holgate 2022), and water

27. Since monitoring stations collect COD concentration information instead of aggregate COD emissions in the river body, we prefer using wastewater emissions with high/medium/low pollutant concentrations as independent variables in the event study.

28. Our data set does not contain information on the all-cause death rate. The percentage is reported in the official document "National Disease Surveillance System Death Reason Dataset 2008"; see https://ncncd.chinacdc.cn/jcysj/siyinjcx/syfxbg.

Table 5. The Health Effects of Establishing Automatic Stations: Considering the Establishment of Upstream Automatic Stations

	Digestive Disease Death Rate		Life Expectancy at Birth	
Dependent Variable	(1)	(2)	(3)	(4)
Establishment of downstream automatic station	−2.469***	−2.341***	2.873***	3.192***
	(.901)	(.871)	(.725)	(.798)
Establishment of upstream automatic station	−1.688	−2.074	1.332	1.347
	(1.289)	(1.322)	(1.645)	(1.639)
Control variables		Yes		Yes
Year fixed effects	Yes	Yes	Yes	Yes
DSP fixed effects	Yes	Yes	Yes	Yes
Number of observations	2,743	2,743	2,688	2,688
Adjusted R^2	.561	.567	.483	.484

Note. This table reports the results of the robustness check that controls for the establishment of upstream automatic stations. The digestive disease death rate is age-adjusted by calculating age-specific death rates and creating weighted averages using the population structure in China's 2010 census. Control variables include a dummy variable indicating the establishment of a downstream manual station, log(GDP per capita), and log(hospital beds per 1,000 residents). Standard errors clustered at the city level are reported in parentheses. DSP = disease surveillance point.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

quality is only a secondary cause. Shown in section 3.2, the establishment of downstream automatic stations only reduces water pollution emissions, rather than air pollution emissions, from upstream counties. Additionally, the last two columns of table 6 show that death rates of all other diseases are not affected either.[29] In sum, the regression results in table 6 further indicate that the establishment of upstream stations mainly increases life expectancy through reducing the death rate of digestive diseases. Finally, the middle and right panels of figure AV indicate that the health DID estimations also pass the falsified timing tests.

4.3. Heterogeneity and Robustness Checks

We further divide digestive diseases into two categories based on the cause of death. Specifically, we reexamine the effects of downstream automatic stations on the death rate from digestive cancers (involving esophagus, stomach, liver, colorectal, and pancreas cancers) and noncancer digestive diseases. The two sets of estimation results in table 7

29. "Other diseases" include malnutrition, low birth weight, and congenital anomalies.

Table 6. The Effects of Establishing Automatic Stations on Other Death Rates

	Death Rate From									
	Placebo: Accidents		Lung Cancer		Respiratory Infection		Cardiovascular Diseases		Other Diseases	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Establishment of downstream automatic station	−.205	−.326	−.497	−.586	.370	.389	.967	−.204	−.195	−.225
	(.226)	(.214)	(.383)	(.389)	(.349)	(.340)	(1.399)	(1.486)	(.209)	(.188)
Control variables		Yes		Yes		Yes		Yes		Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DSP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	2,743	2,743	2,743	2,743	2,651	2,651	2,743	2,743		
Adjusted R^2	.471	.475	.424	.424	.416	.416	.536	.542	.227	.226

Note. This table reports the effects of establishing automatic stations' effects on death rates of accident (placebo test), lung cancer, respiratory infection, cardiovascular disease, and other diseases. Death rates are age-adjusted by calculating age-specific death rates and creating weighted averages using the population structure in China's 2010 census. Control variables include a dummy variable indicating the establishment of a downstream manual station, log(GDP per capita), and log(hospital beds per 1,000 residents). Data from two disease surveillance points (DSPs) are dropped from the sample for the regressions of cardiovascular diseases due to the abnormally large death rate records in some years. Standard errors clustered at the city level are reported in parentheses.

show that the health effect of water-quality improvement is all-round: the death rates of patients with both types of illness decline, which again confirms the necessity of increasing monitoring capability powered by automatic reporting technologies.

Besides, separately studying the effects on digestive cancer and noncancer digestive diseases also helps enhance the credibility of the estimated health benefits. Figure 10 conveys two messages that are both consistent with medical research. First, the death rate from noncancer digestive diseases starts to decline earlier than that from digestive cancer, and it declines at a faster rate than that from digestive cancer during the first few years following station establishment. This is consistent with the findings in the medical literature that acute digestive diseases are typically more sensitive to environmental quality in a short time window (Morales-Suarez-Varela et al. 1995; Jalan and Ravallion 2003; Robins-Browne et al. 2004). Second, the death rate from digestive cancers keeps declining, while that from noncancer digestive diseases stabilizes in three years. This finding is again reasonable as cancers are slow-growing (Nyberg et al. 2000; Pope et al. 2002; Ebenstein 2012). Therefore, water quality improvement has a gradual but long-lasting effect on the death rate from digestive cancers, which is in sharp contrast with the effect on noncancer digestive diseases.

Table 7. Effects of Automatic Stations on Digestive Diseases Death Rate: By Causes

	Death Rate From			
	Digestive Cancer		Noncancer Digestive Disease	
	(1)	(2)	(3)	(4)
Establishment of downstream automatic station	−1.873***	−1.752**	−.514*	−.505*
	(.712)	(.722)	(.285)	(.272)
Control variables		Yes		Yes
Year fixed effects	Yes	Yes	Yes	Yes
DSP fixed effects	Yes	Yes	Yes	Yes
Number of observations	2,743	2,743	2,743	2,743
Adjusted R^2	.574	.580	.654	.655

Note. This table reports the effects of automatic stations on the digestive disease death rate by causes. Digestive cancer death rate and noncancer digestive disease death rate are both age-adjusted by calculating age-specific death rates and creating weighted averages using the population structure in China's 2010 census. Control variables include a dummy variable indicating the establishment of a downstream manual station, log(GDP per capita), and log(hospital beds per 1,000 residents). Standard errors clustered at the city level are reported in parentheses.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

According to the World Bank (2007), a large share of the population in China did not have access to adequate sanitary facilities in the early twenty-first century, our major sampling period. The tap water coverage rate was still relatively low, with the average rate across all counties in China being around 50% in 2004 (World Bank 2007). Industrial wastewater dumping has largely rendered surface water in rivers and lakes unfit for human consumption (Ebenstein 2012). Given that surface water is the major drinking water source in the country,[30] individuals are less vulnerable to ambient water pollution if they gain access to tap water that is usually pretreated by treatment facilities before being delivered to households (Ebenstein 2012). Automatic stations, through monitoring the quality of water heavily affected by wastewater dumping, have the potential to purify drinking water for those who do not have access to tap water. Therefore, we expect the health effects of establishing automatic stations to be smaller with higher tap water coverage. The tap water coverage data we collected are from China's population census data of 2000, where the tap water coverage levels in each county/district in the year 2000

30. A recent report by the Asia Pacific Foundation of Canada shows that China gets 63% of its drinking water from surface water sources. See https://www.asiapacific.ca/blog/china-eco-city-tracker-upstream-battle-drinkable-water.

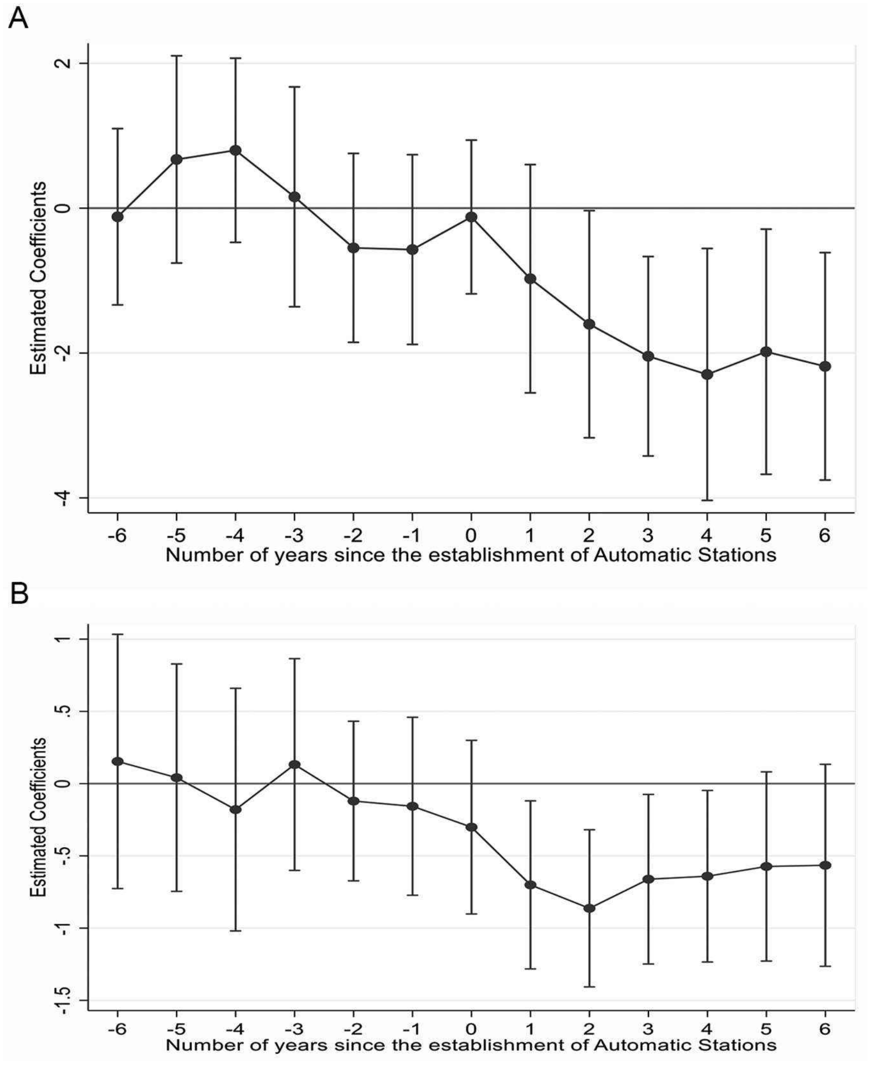

Figure 10. The dynamic effects of establishing automatic stations on death rates of digestive cancer (*A*) and noncancer digestive diseases (*B*). The figure plots the results of the event study regressions where the dependent variables are death rates of digestive cancer (*A*) and noncancer digestive diseases (*B*). Standard errors are clustered at the city level. The horizontal axis measures the number of years since the establishment of automatic stations. The plots connected by the solid line indicate changes in death rates of digestive cancer (*A*) and noncancer digestive diseases (*B*) compared to seven or more years before the establishment of automatic stations conditional on year fixed effects, disease surveillance point (DSP) fixed effects, the establishment of manual stations, lagged log(GDP per capita), and lagged log(hospital beds per 1,000 residents). Color version available as an online enhancement.

are reported. We categorize DSPs into two groups: those where the proportion of households accessing tap water is below the national average (low tap water samples) and those where that is above the national average (high tap water samples). We then reestimate equation (3) using low and high tap water samples separately. Following Ebenstein (2012), we additionally include urban-year fixed effects to control for the possibility that tap water coverage may be generally higher in urban areas, so that the confounding effect of urban- (rural-) specific health determinants would be teased out from the estimated treatment effect. The estimation results are reported in table 8.

Notably, the estimated coefficients of the downstream automatic station dummies are negative and statistically significant for low tap water samples (cols. 1 and 2), and the effects are smaller and statistically insignificant for high tap water samples (cols. 3 and 4). This relatively large difference is as expected because the tap water coverage rate exhibits considerable dispersion in our sample: the average coverage rates for the low- and high-coverage subsamples are 25% and 81%, respectively. The large dispersion of

Table 8. The Effects of Establishing Automatic Stations on Digestive Disease Death Rate: Low Tap Water and High Tap Water Sample

	Dependent Variable: Digestive Disease Death Rate			
	Low Tap Water Sample		High Tap Water Sample	
	(1)	(2)	(3)	(4)
Establishment of downstream automatic station	−3.711**	−3.402**	−1.256	−1.356
	(1.614)	(1.533)	(.813)	(.888)
Control variables		Yes		Yes
Urban-year fixed effects	Yes	Yes	Yes	Yes
DSP fixed effects	Yes	Yes	Yes	Yes
Number of observations	1,242	1,242	1,501	1,501
Adjusted R^2	.585	.590	.545	.554

Note. This table examines the heterogeneous treatment effects of establishing automatic stations on digestive disease death rate based on county-level tap water adoption rate. Columns 1 and 2 include disease surveillance points (DSPs) located in counties where the proportion of households drinking tap water is lower than the national average, and cols. 3 and 4 include DSPs located in counties where the proportion of households drinking tap water is higher than the national average according to China's 2000 census. Control variables include a dummy variable indicating the establishment of downstream manual station, log (GDP per capita), and log(hospital beds per 1,000 residents). Urban-year fixed effects are included to control for potential selection effect originating from the possibility that the tap water coverage rate is in general higher in urban areas. Standard errors clustered at the city level are reported in parentheses.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

tap water coverage rates and the pronounced difference between treatment effects for high- and low-coverage counties also implies that the expansion of the automatic station network helps to improve regional equality. Besides, the reasonable heterogeneous effects for the counties with different levels of tap water coverage further enhance the credibility of the estimated health benefits.

We further experiment with adopting alternative upstream and downstream designation methods. Similar to the alternative method used in section 3.3, we categorize DSPs into treatment and control groups based on whether the group is located within 100 km from an automatic station and whether it is upstream or downstream from the automatic station. The impacts of establishing downstream automatic stations on digestive disease death rates and life expectancy at birth are then estimated, and the results are reported in columns 3–6 in table AVIII. Our estimation results are also robust to alternative upstream and downstream DSP designation methods.

Finally, we also experiment with the extended difference-in-differences estimator proposed by Callaway and Sant'Anna (2021) for the health regression. The results, reported in columns 8–9 of table AIX, are similar to the main results in both magnitude and significance level.

4.4. Additional Discussions

It might be helpful to further monetize the mortality reduction reported in section 4.1. The average population across the treated DSPs during the sampling period is 280,000; therefore, establishing a downstream automatic station reduces death from digestive diseases by 65 persons for an average county (i.e., 2.341 × 28). Using an estimated value of a statistical life (VSL) at 2.26 million RMB per person (Qin et al. 2013), the monetized benefit from establishing automatic stations amounts to 148 million RMB (i.e., 2.26 × 65) for the average county. Besides, the installation cost of automatic stations is around 1 million RMB per station,[31] which is relatively low compared to the health benefit. Meanwhile, the stricter enforcement of environmental regulations also reduced industrial output in the average county by 57 million RMB.[32] Based on these estimates, a simple back-of-envelope analysis further implies that establishing automatic stations brings about 90 million RMB net benefit annually to an average affected county. According to our benefit-cost analysis, considerable welfare gain across the country should have materialized following the recent expansion of automatic station coverage since 2012, the last year in our sampling period.

Establishing automatic stations represents a particular form of effective policy enforcement. There are definitely other enforcement innovations, such as direct environmental

31. See http://www.ccgp.gov.cn.

32. Although the reduction in output is statistically insignificant, end-of-pipe emissions abatement that has little impact on firm output might have played an important role. The output results are available upon request.

inspections by the central government and third-party auditing. There is no single panacea, however, for the compliance problem. For example, Duflo et al. (2013) show that traditional third-party emissions auditing in India is heavily corrupted, and auditors typically underreport plants' emissions. Similarly, Lin and Sun (2023) and Hu (2022) show that the effect of China's recent Central Environmental Protection Inspection (CEPI) is largely transient: although environmental quality improved during the inspection, emissions quickly bounced back after the inspection team left.

Compared to these other enforcement actions, the central government and the public can access the real-time readings of automatic stations at any time, which ensures a long-lasting effect of establishing automatic stations. Although the 1 million RMB installation cost may seem high for many developing countries, the fact that the monetized health benefit far exceeds the installation cost justifies considering enforcement with advanced technologies. Besides, different enforcement strategies may also complement each other, and enforcement coordination may further improve the effectiveness of establishing automatic stations. We leave the study of enforcement coordination to future research.

5. CONCLUSIONS

We have shown that the establishment of automatic stations in China significantly reduces wastewater emissions in their upstream areas. Moreover, we have also shown that the establishment of automatic stations significantly reduces the death risk of digestive diseases in their upstream areas, and then, the life expectancy at birth significantly lengthens.

Monitoring is one of the key components that regulators use to enforce and ensure that the regulated communities obey environmental regulations. With traditional field inspections, the monitoring capacities are very limited. Our study illustrates how the adoption of advanced monitoring technologies enhances the enforcement of environmental regulations. Advanced monitoring technologies (e.g., the real-time monitoring and electronic-reporting technologies) integrate many characteristics of the "next generation" of environmental compliance and enforcement as thinking has been centered on enhanced information transparency. The adoption of advanced monitoring technologies considerably increases information transparency and provides regulators and the public the access to more complete, timely, and readily available information about compliance and environmental outcomes of regulated entities and, therefore, would enhance the enforcement and compliance with environmental regulations.

Particularly in developing countries where the enforcement of environmental regulations is often considered weak, the environmental quality is then poor, and the associated health costs are massive, the adoption of advanced monitoring technologies might enhance the enforcement and compliance to a large extent and result in notable improvements in the environment, human health, and social welfare.

Finally, our study investigates the potential health benefits associated with the adoption of automatic water quality monitoring technology. Besides water quality monitoring, automatic information collection systems have also been widely adopted to monitor air quality in China. According to our case study of water pollution monitoring, the automatic air quality monitoring stations may have also induced nontrivial welfare gain. A natural extension of this study is to quantify the health benefits associated with automatic air quality monitoring to get a more comprehensive understanding of the benefits of applying advanced information technologies in policy enforcement.

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