WATERING DOWN ENVIRONMENTAL REGULATION IN CHINA*

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Abstract

This paper estimates the effect of environmental regulation on firm productivity using a spatial regression discontinuity design implicit in China's water quality monitoring system. Because water quality readings are important for political evaluations, and the monitoring stations only capture emissions from their upstream regions, local government officials are incentivized to enforce tighter environmental standards on firms immediately upstream of a monitoring station, rather than those immediately downstream. Exploiting this discontinuity in regulation stringency with novel firm-level geocoded emission and production datasets, we find that immediate upstream polluters face a more than 24% reduction in Total Factor Productivity (TFP), and a more than 57% reduction in chemical oxygen demand emissions, as compared to their immediate downstream counterparts. We find that the discontinuity in TFP does not exist in non-polluting industries, only emerged after the government explicitly linked political promotion to water quality readings, and was predominantly driven by prefectural cities with career-driven leaders. Linking the TFP estimate with the emission estimate, a back of the envelope calculation indicates that China's water regulation efforts between 2000 and 2007 was associated with an economic cost of more than 800 billion Chinese yuan.

Keywords: political incentives; total factor productivity; water quality monitoring; water pollution; environmental policy; COD (JEL: Q56, Q58, O13, O44, D24)

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I. Introduction

In developing countries such as China and India, billions of people live under extreme pollution every day, while still being economically dependent on dirty manufacturing industries (Greenstone and Hanna, 2014; Ebenstein et al., 2017). However, little is known about the economic costs of alleviating pollution in these settings: existing research has mainly focused on the U.S., which sheds limited light on the developing world, where the cost of environmental regulation might vary substantially due to differences in industrial structures and factor endowments (Basu and Weil 1998), as well as political institutions and bureaucratic incentives (Acemoglu and Robinson, 2013; Greenstone and Jack, 2015).

Our paper fills in this important gap in knowledge by studying China, the world's largest emitter and manufacturer, where a unique empirical setting is created by the central government's use of high-powered political incentives to enforce environmental regulation. To tackle China's severe water pollution problems, the central government installed a few hundred state-controlled water monitoring stations along the major national river trunks and used the water quality readings to help determine the promotion of local government officials. However, this political contract between central and local governments is undermined because of imperfect monitoring: water monitoring stations can only capture emissions from upstream, which gives local officials spatially discontinuous incentives to enforce tighter regulations on polluters located immediately upstream of monitoring stations, as compared to their immediately downstream counterparts.

Exploiting this spatial discontinuity in regulation stringency, we find that polluting firms immediately upstream of monitoring stations have more than 24% lower total factor productivity (TFP), and more than 57% lower chemical oxygen demand (COD) emissions, as compared to polluting firms in the near downstream. Further investigation shows that these findings cannot be explained by the endogenous location choices of monitoring stations, nor by the endogenous sorting of polluting firms. Instead, our evidence consistently suggests that the spatial discontinuity is indeed driven by upstream firms receiving tighter water regulation enforcement: the upstream-downstream TFP gap exists only in polluting industries rather than non-polluting industries, and is predominantly caused by upstream polluters investing more heavily in (non-productive) abatement equipment and making costly adjustments to clean up their production processes.[1] To put the magnitude of our findings in context, the estimated upstream-downstream TFP gap is comparable to two years of average TFP

[1] Intuitively, investments in "abatement equipment" and "cleaner production process" are important capital inputs for firms, but they do not lead to increases in output. The regulated firms are producing less output for a given amount of inputs, and therefore have lower total factor productivity. We formalize this intuition with a simple model in Appendix A, and use it to guide the empirical investigation.

growth for Chinese manufacturers during our sample period (2000-2007),[2] and a back of the envelope calculation for the entire country suggests that water regulation costed more than 110 billion Chinese yuan per year in industrial value-added.

In addition to allowing us to quantify the economic costs of improving water quality, the salient spatial discontinuity in regulation enforcement also demonstrates a fundamental issue with political centralization: when the central government relies on local governments to implement national programs, it often promises political rewards contingent on meeting certain performance criteria. However, given the ubiquitous information asymmetry between the central and local governments, many important dimensions of performance cannot be accommodated in the political contract. As a result, local officials will exert efforts on the "contractable" dimensions while shirking on those "non-contractable" dimensions, thus distorting the well-intended central policies in unexpected and potentially costly ways (Kornai, 1959; Nove and Nove, 1969).[3] In our context, the central government intends to improve overall water quality, but can only observe water quality readings that reflect upstream emissions. As a result, decentralized regulation enforcement deviates from the central government's original intention, by prioritizing "water quality readings" over "actual water quality," creating immense spatial inequalities in regulatory burden and pollution exposure.

This political economy interpretation is strongly supported by a rich set of empirical results: (1) the upstream-downstream gap only emerged immediately after 2003, when the central government started to link water quality readings to political promotions; (2) the upstream-downstream gap is predominantly driven by prefectural cities with politically motivated leaders, and there is no significant spatial discontinuity when the local leaders don't have promotion prospects; (3) only polluters within a few kilometers upstream are regulated, as emissions from farther upstream would dissipate quickly over space and have negligible impact on water quality readings; (4) upstream firms pay higher amounts of emission fees than downstream firms, although they actually emit significantly less, implying that local officials hold double standards in regulation enforcement; (5) the upstream-downstream gap gets particularly large when the monitoring stations are "automated" and therefore less susceptible to data manipulation, suggesting that local officials used to manipulate water quality readings for those traditional "manual" stations. Taken together, these findings consistently confirm that the salient spatial discontinuity in regulation enforcement arose from the misalignment between the national policy goal and local bureaucratic incentives.

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[2] With the same dataset and same method for TFP estimation, Brandt, Van Biesebroeck, and Zhang (2012) finds that the average TFP growth among Chinese manufacturing firms in 2005 was 14%.

[3] This idea relates more generally to the contract theory literature on multi-tasking (Holmstrom and Milgrom, 1991; Hart, Shleifer, and Vishny, 1997).

Our paper speaks to several strands of literature. First and foremost, we provide the first rigorous and comprehensive empirical evidence on the economic costs of environmental regulation in a developing economy. While there exists a large empirical literature on how environmental regulation affects firm productivity (Jaffe et al., 1995; Berman and Bui, 2001; Greenstone, 2002; Greenstone, List, and Syverson, 2012) and other economic outcomes (Henderson, 1996; Becker and Henderson, 2000; Walker, 2011; Ryan, 2012; Kahn and Mansur, 2013; Walker, 2013), they have focused almost exclusively on developed countries. In sharp contrast, little systematic knowledge exists on the environment-economy tradeoff in the developing world, despite the tremendous policy implications. To fill in this gap, we investigate the largest polluter and manufacturer in the world and highlight the enormous economic costs of environmental regulation in such a rapidly growing economy.[4]

Second, our paper adds to the long-standing discussion on the political economy of centralized regimes. By documenting the substantial upstream-downstream gap in regulatory burden, we provide direct evidence that over-centralization in political power can create salient distortions in decentralized policy implementation (Kornai, 1959; Nove and Nove, 1969). Relatedly, the existing literature attributes China's success with economic decentralization to its strong political centralization, which helps the central government ensure that local governments stay aligned with national policy goals (Blanchard and Shleifer, 2001; Xu, 2011). Our paper complements this conventional wisdom by showing that such central-local alignment might break down in the presence of imperfect performance monitoring. More specifically, this paper also relates to a growing literature on the political economy of pollution (List and Sturm, 2006; Burgess et al., 2012; Kahn, Li, and Zhao, 2015; Lipscomb and Mobarak, 2017; Jia, 2017) by shedding light on how China's environmental regulations are implemented at the local level.

Third, due to both data and identification challenges, the literature on environmental regulation has focused on air pollution, while water pollution remains under-researched, as pointed out by Keiser and Shapiro (2019b). The existing work on water pollution focuses on the environmental benefits of water regulation (e.g., Greenstone and Hanna, 2014; Keiser and Shapiro, 2019a,b), while the associated economic costs are typically computed using either engineering-type estimates or government expenditure records, missing an important component of emission abatement cost: the impacts of water regulation on production activities. To fill in this gap, our paper investigates the impacts of water

[4] One closely related study is Cai, Chen, and Gong (2016), which documents that Chinese provinces have incentives to "pollute their neighbors" by allowing the furthest downstream counties to engage in more water-polluting production activities. Our paper complements Cai, Chen, and Gong (2016) by causally identifying the "intensive margin" effect of regulation on firm performance (while teasing out the "extensive margin" effect of regulation on firm sorting). Combined with our firm-level emissions results, this allows us to compute the average abatement costs for the entire Chinese manufacturing sector.

regulation on both TFP and COD emissions, and estimates that a 10% reduction in COD emissions leads to a 3.38% decrease in TFP. Based on this estimated "average abatement cost," our calculation suggests that China's regulation of industrial COD emissions between 2000 and 2007 was associated with an economic cost of more than 800 billion Chinese yuan.

The rest of this paper is structured as follows. Section II describes the institutional background and research design. Section III introduces the data and presents descriptive statistics. Section IV presents the baseline findings, and addresses the potential threats to our empirical analysis. Section V explores how upstream firms respond to tighter regulation, with a focus on their emission abatement strategies. Section VI investigates the political economy of decentralized regulation enforcement. Section VII benchmarks the economic significance of our findings. Section VIII concludes.

II. Background and Research Design

A. Water Quality Monitoring and Water Pollution Controls in China

In the late 1990s, after nearly two decades of unprecedented growth in industrial manufacturing, China started to face a variety of pressing environmental challenges, including deteriorating surface water quality. According to the World Bank (2007), in 2000, roughly 70 percent of China's rivers contained water deemed unsafe for human consumption. Severe water pollution led to tremendous health costs, such as significantly increased rates of digestive cancer (Ebenstein, 2012) and infant mortality (He and Perloff, 2016). Seeing the growing social unrest associated with surface water pollution, the Chinese central government started its attempts to protect water bodies and reverse the process of degradation.

To gather surface water quality information, the Ministry of Environmental Protection (MEP) established a national water quality monitoring system in the 1990s, known as the "National Environmental Quality Monitoring Network – Surface Water Monitoring System" (NEQMN-SWMS). Under the NEQMN-SWMS, water monitoring stations were built to collect various measures of water pollution in all the major river segments, lakes, and reservoirs in China and to report the water quality grade to the MEP.

In the 1990s, GDP growth was considered the national priority, and the central government did not set strict emission abatement and water grade improvement targets for the local government officials.[5] The monitoring network was thus considered to serve mostly scientific rather than regulatory purposes,

[5] In the "9th Five-Year Plan" of the central government (1996-2000), no explicit goals for emission reduction and water quality readings were mentioned.

and the monitoring stations were located in a way that was spatially representative of neighboring water bodies to properly reflect changes in water pollutants over time. Consequently, the locations of the monitoring stations were mainly determined by hydrological factors (the depth, speed, and width of surface water and the soil characteristics of riverbanks), and many of them were built upon the existing hydrological stations.[6]

In 2002, Hu Jintao took over the presidency from Jiang Zemin. Given the country's mounting environmental challenges, Hu started to emphasize the importance of seeking a balance between economic growth and environmental sustainability. Most notably, in 2003, Hu formally proposed the "Scientific Outlook of Development" (SOD), which sought integrated sets of solutions to economic, environmental, and social problems, starting an era of aggressive environmental regulation in China.[7]

Following the SOD agenda in 2003, the Ministry of Environmental Protection (MEP) quickly increased its efforts to reduce water pollution: it issued a series of regulatory documents to the local governments, highlighting the importance of water quality readings in surface water regulation.[8] Specifically, the MEP imposed explicit water quality targets for all the state-controlled stations at the time and started automating the monitoring stations along the large rivers and lakes to improve data quality. To further engage the public, the MEP also started to systematically publicize water quality readings from all state-controlled stations.

Throughout President Hu's tenure (2002-2012), the importance of clean surface water was emphasized repeatedly, and the central government adopted a target-based abatement system to mobilize local politicians for environmental protection. For example, the central government's 10th Five-Year Plan (2001-2005) required that national COD emissions should be reduced by 10% and that more than 60% of water quality readings should be up to standard based on the functional zoning of the corresponding river body.[9] During the 11th Five-Year Plan (2006–2010), the water emission abatement targets included (but were not limited to): (1) reducing COD emissions by 10%; (2) ensuring that by 2010, no more than 22% of monitored water sections would fail to meet Grade V National Surface Water Quality Standards; and (3) ensuring that at least 43% of the monitored water sections

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[6] This rule allows the local governments to combine hydrological parameters with water quality readings and pool resources from both types of stations. In Appendix B, we provide more institutional background about the location choices of the water quality monitoring stations.

[7] The SOD is generally regarded as President Hu's most important policy agenda and political legacy. It was subsequently included in the revised versions of the "Constitution of the Chinese Communist Party," the "Guiding Thoughts of the Chinese Communist Party," and the "Constitution of the People's Republic of China."

[8] For example, in 2003, the MEP issued the "Technical Specification Requirements for Monitoring of Surface Water and Wastewater" to local governments and specified detailed requirements on monitoring and improving water quality across the country.

[9] http://www.gov.cn/gongbao/content/2002/content_61775.htm

(of the seven main bodies of water in China) would meet Grade III National Surface Water Quality Standards by 2010.[10]

To meet these targets, the central government assigned abatement requirements to each province, and provincial governors were required to sign individual responsibility contracts with the central government, documenting their emission abatement plans and commitments in detail. Provincial governors further assigned strict abatement mandates to prefecture and county leaders and incorporated these environmental targets as important criteria in determining their promotion cases. Given such high-powered political incentives, large polluting industrial firms became the target of local government officials, as their emissions are the largest contributor to local water pollution.

We examined a large body of policy documents on how different levels of governments interfere with industrial firms to improve water quality readings. As discussed in greater detail in Appendix D, these files suggest that many local governments, by threatening polluting firms with "production suspension" and "temporary shutdown," are able to coerce them to invest heavily in abatement equipment and make adjustments to clean up their production processes. While these capital investments to abate emissions account for a large proportion of firm input, they contribute little to output production. As a result, these regulated firms are expected to see a reduction in total factor productivity (TFP), which measures the amount of output obtained from a given set of inputs (Syverson, 2011). This idea is formalized by the model presented in Appendix A.

Under the local officials' efforts to regulate polluting firms and abate water pollution, China's surface water quality indeed improved dramatically after 2003. In Panel A of Figure I, we plot the average water quality grades for a balanced panel of monitoring stations between 2000 and 2007.[11] We observe water readings getting slightly worse before 2002, and then starting to improve rapidly after 2003, when the government started to emphasize surface water protection. From 2002 to 2007, average water quality reading improved by a grade of more than 0.6. Based on the estimates of Ebenstein (2012), such an improvement would imply a 5.8% reduction in the national digestive cancer rate. In Panel B of Figure I, we also plot the yearly national industrial COD emissions between 2000

[10] Source: http://www.mep.gov.cn/gzfw_13107/zcfg/fg/gwyfbdgfxwj/201605/t20160522_343144.shtml

[11] The overall surface water quality in China is graded on a 6-point scale, where Grade I water is of the best quality and Grade VI is of the worst. According to the Ministry of Water Resources, Grade I means an "Excellent" source of potable water. Grade II means a "Good" source of potable water. Grade III water is considered "Fair." Pathogenic bacteria and parasites' ova can sometimes be found in Grade II and III water, so drinking it will introduce pathogens to human consumers. Thus, Grade II and III water should be purified and treated (such as by boiling) before drinking. Grade IV water is polluted and unsafe to drink without advanced treatment, which is only possible at water supply plants. Grade V water is seriously polluted and cannot be used for human consumption. Grade VI water is considered "Worse than Grade V Water," and any direct contact with it is harmful to humans.

and 2007, and see a very similar pattern: annual industrial COD emission was stable before 2002, and suddenly started to drop after 2003.

Because rivers flow from higher to lower elevation, water quality monitoring stations can only detect emissions from upstream. When the central government imposed high political stakes on the readings of water monitoring stations, the local officials would have strong incentives to regulate polluters in the immediate upstream of a monitoring station, but little incentive to regulate polluters in the immediate downstream. Meanwhile, because the Chinese government did not enforce stringent water pollution controls until 2003, we expect that the productivity gap between upstream and downstream polluting firms was minimal before 2003, and enlarged substantially afterward.

B. Research Design and Econometric Model

We exploit the spatial discontinuity in regulatory stringency around water monitoring stations to estimate the causal effect of regulation on TFP. The distance between a firm and a monitoring station serves as the running variable. We examine whether firms located immediately upstream from the monitoring station have lower productivity than adjacent downstream firms. This empirical strategy is related in spirit to recent works exploiting the flow of pollution along rivers for identification (Keiser and Shapiro, 2019a; Lipscomb and Mobarak, 2017), but is novel in that it utilizes a unique spatial discontinuity setting around the monitoring stations, which is created by the Chinese central government's efforts in leveraging high-powered political incentives for the decentralized enforcement of environmental regulations.

The identifying assumption of our research design is that, due to spatial adjacency, firms located immediately upstream and downstream of monitoring stations should be *ex-ante* identical, but will later on differ from each other as upstream firms face tighter regulation. As discussed in the previous section, the water monitoring stations were located based on hydrological factors before water quality readings became a political priority, which suggests that our identifying assumption is likely satisfied.

The discontinuity can be estimated by both parametric and non-parametric approaches. Gelman and Imbens (2019) show that the parametric RD approach, which uses a polynomial function of the running variable as a control in the regression, tends to generate RD estimates that are sensitive to the order of the polynomial and have some other undesirable statistical properties. Therefore, we rely on the recommended local linear approach, and estimate the following equation:

(1) $$TFP_{ijk} = \alpha_1 Down_{ijk} + \alpha_2 Dist_{ijk} + \alpha_3 Down_{ijk} \cdot Dist_{ijk} + u_j + v_k + \varepsilon_{ijk}$$

$$s.t. \ -h \leq Dist_{ijk} \leq h$$

where TFP_{ijk} is the total factor productivity of firm *i* in industry *j* around monitoring station *k*. $Down_{ijk}$ is an indicator variable that equals 1 if firm *i* (in industry *j*) is downstream from monitoring station *k*, and 0 otherwise. $Dist_{ijk}$ measures the distance between firm *i* and monitoring station *k* (negative if upstream and positive if downstream), and h is the estimated MSE-optimal bandwidth following Calonico, Cattaneo, and Farrell (2018). The standard error is clustered at the monitoring station level to deal with the potential spatial correlation of the error term, as suggested by Cameron and Miller (2015).

To account for the industry- and location-specific TFP determinants in the non-parametric estimations, we control for industry and monitoring station fixed effects u_j and v_k in the baseline model. The estimation of this non-parametric RD model with fixed effects is implemented using the two-step approach suggested by Lee and Lemieux (2010), where industry and station fixed effects (or industry-by-station fixed effects in a more saturated model) are absorbed by running an OLS regression of TFP on a set of industry and station-specific dummies, and then applying the non-parametric estimations on the residualized TFP.[12]

We augment the baseline econometric specification in several different ways: (1) controlling for industry-by-station fixed effects; (2) leveraging the panel structure of our data and absorbing firm fixed effects, which allows us to estimate the treatment effect using only within-firm variation; (3) combining polluting and non-polluting industries in a unified model and directly estimate the heterogeneous treatment effect; and (4) estimating a parametric RD model with various polynomials of the running variable. As will be elaborated in more detail in the following sections, our main findings go through in all these alternative models.

III. Data and Summary Statistics

A. Data

In this paper, we combine several novel datasets that together provide comprehensive information on the socio-economic conditions of townships, production and performance of industrial firms, and emissions from heavy polluters centered around water monitoring stations.

Water Quality Monitoring Stations

[12] Lee and Lemieux (2010) argue that, if there is no violation of the RD assumption that unobservables are similar on both sides of the cutoff, using a residualized outcome variable is desirable because it improves the precision of estimates without causing bias.

We collect information on water quality monitoring stations from surface water quality reports in various environmental yearbooks from 1999-2010, which include the China Environmental Yearbooks, China Environmental Statistical Yearbooks, and China Environmental Quality Statistical Yearbooks. Data available in more than two different sources are cross-validated. The number of state-controlled monitoring stations varied slightly between years in these reports, ranging from 400 to 500 stations. We geocoded all the water quality monitoring stations.[13]

Annual Survey of Industrial Firms

Our firm-level production information is based on the Annual Survey of Industrial Firms (ASIF) from 2000 to 2007. The ASIF data include private industrial enterprises with annual sales exceeding 5 million RMB and all the state-owned industrial enterprises (SOEs). The data are collected and maintained by the National Bureau of Statistics (NBS) and contain a rich set of information obtained from the accounting books of these firms, such as inputs, outputs, sales, taxes, and profits.

The ASIF data is widely used by empirical researchers, and a well-known issue is that the data contain outliers. We follow standard procedures documented in the literature to clean the data. We first drop observations with missing key financial indicators or with negative values for value-added, employment, and capital stock. We then drop observations that apparently violate accounting principles: liquid assets, fixed assets, or net fixed assets larger than total assets; or current depreciation larger than cumulative depreciation. Finally, we trim the data by dropping observations with values of key variables outside the range of the 0.5^{th} to 99.5^{th} percentile.[14]

The ASIF data have detailed address information for sampled firms in each year. We geocode the location of the 952,376 firms that appeared in the sample and then compute the distance between each firm and its closest water quality monitoring station.[15] Nearly 5% of the firms in the ASIF database belong to a parent multi-unit firm; we exclude them from subsequent analyses because the parent firm might avoid regulation by reallocating production activities across its subordinate firms.

The detailed production information allows us to measure firm-level productivity for the entire Chinese manufacturing sector. While there are various approaches to measure total factor productivity, it has been documented in the literature that these measures are in general highly correlated with each other (Syverson, 2011). In this paper, we rely on the semi-parametric estimator suggested by Olley and Pakes (1996) to construct our baseline TFP measure, which addresses the simultaneity and

[13] For monitoring stations built before 2007, we are unable to obtain the exact timing of station construction. So, in the baseline analysis between 2000 and 2007, we focus only on stations already existing in 2000. We use stations constructed after 2007 as a placebo test.

[14] More details about the construction and cleaning processes of the ASIF data can be found in Brandt, Van Biesebroeck, and Zhang (2012), and Yu (2015).

[15] Township coordinates are used when the detailed when firm address cannot be precisely geocoded.

selection biases in estimating the labor and capital coefficients, and has been the most widely used method for the investigation of Chinese firms' productivity (e.g., Brandt, Van Biesebroeck, and Zhang, 2012; Yang, 2015). Using the Olley-Pakes approach therefore ensures that our findings can be benchmarked by the existing estimates in the literature. The capital and labor coefficients are estimated by each industry, year fixed effects are included in every regression to control for industry-year level production dynamics, and "whether a firm is in the near upstream of a monitoring station" is included as a state variable to take into account that upstream polluters might be forced to install more abatement facilities by the government. The procedures of our key variable construction and Olley-Pakes estimation are discussed in more detail in Appendix C. The estimated labor and capital coefficients for each industry are reported in Appendix Table S1.

The ASIF firms can be categorized into polluting industries and non-polluting industries based on the official definition of the MEP.[16] Because our baseline spatial discontinuity design is essentially cross-sectional, in the main analysis, we collapse the multi-year panel data into a cross-section and estimate the RD model. The interpretation of the coefficient is therefore the average effect that persists during the sample period (2000-2007). To better understand the dynamics of regulation enforcement, we first estimate the RD model separately for each year, and then fully utilize the panel structure of our data and estimate a "Difference-in-Discontinuities" model, which exploits only within-firm variation (before and after 2003) for identification.

Environmental Survey and Reporting Database

To investigate whether water quality monitoring indeed reduces water-related emissions, we collect firm-level emission data from the Environmental Survey and Reporting (ESR) database, which is managed by the MEP.

The ESR provides the most comprehensive environmental data in China that monitors polluting activities of all major polluting sources, including heavily polluting industrial firms, hospitals, residential pollution discharging units, hazardous waste treatment plants, and urban sewage treatment plants. In this study, we focus on the ESR firms that are in the same polluting industries as the ASIF firms.

The sampling criteria in the ESR database are based on the cumulative distribution of emissions in each county. Polluting sources are ranked based on their emission levels of COD and sulfur dioxide (SO_2), and those jointly contributing to the top 85% of total emissions in a county are included in the database. In this study, we use ESR data between 2000 and 2007, the same period as the ASIF database.

[16] Details of the polluting and non-polluting industries are summarized in Appendix Table S2. The 16 polluting industries defined by the MEP account for roughly 80% of China's total industrial COD emissions.

For every firm included in the ESR dataset, total output value, as well as various types of pollutant emissions, are documented. This enables us to construct total emission levels and emission intensity measures (emission levels divided by total output value) for large polluters across China. The ESR data is first self-reported by each polluter, and then randomly verified by government auditors. To ensure data quality for policy-making, the Environmental Protection Law explicitly states that the ESR data cannot be used as the basis for punishing and regulating the polluting firms. As a result, the polluting firms covered in the ESR sample have little incentive to misreport their emission records.

Among the different types of pollutants measured for each ESR firm, chemical oxygen demand (COD) is the most relevant one for this study. COD measures the amount of oxygen required to oxidize soluble and particulate organic matter in water and is widely used as an omnibus indicator for water pollution.[17] A higher COD level indicates a greater amount of oxidizable organic material in the sample, which reduces dissolved oxygen levels. A reduction in dissolved oxygen can lead to anaerobic conditions, which are deleterious to higher aquatic life forms. As discussed in Section II, COD is also the "target pollutant" in China's surface water quality standards: the central government explicitly set a 10% abatement target for COD emissions in the 10th and 11th Five-Year Plans (2001–2005 and 2006–2010).

In addition to COD emissions, we corroborate the firm emissions results by looking at two additional measures of water pollution: ammonia-nitrogen (NH_3-N) emissions and wastewater discharge.

Township-level Socioeconomic Data

The National Bureau of Statistics (NBS) conducts the "Township Conditions Survey" (TCS) on an annual basis. It is a longitudinal survey that collects township-level socio-economic data for all the townships in China. We have access to the TCS data for 20 provinces in 2002 and use the township-level data to assess similarities between upstream and downstream townships.

Geo-data

We obtained township-level GIS boundary data in 2010 from the National Bureau of Statistics. We use GIS data on China's water basin system from the Ministry of Water Resources. We use GIS elevation data to identify upstream and downstream relationships. These GIS datasets are then matched to our geocoded township and firm datasets.

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[17] Among the handful of economic studies focusing on water quality, Sigman (2002) and Lipscomb and Mobarak (2017) use biochemical oxygen demand (BOD); Duflo et al. (2013) use BOD and COD (as well as several other indicators); and Keiser and Shapiro (2019a) focus on "dissolved oxygen" and whether water is safe for fishing.

B. Data Matching

The data we have compiled are, to the best of our knowledge, the most comprehensive and disaggregated collection ever assembled on firm-level economic and environmental performance in China. The matching process involves several steps and is illustrated in Figure II.

First, we keep only monitoring stations located on river trunks and drop those located on lakes and reservoirs, as they would not allow us to identify the upstream-downstream relationship. Then, we put a layer of the water basin system on the township GIS map and keep only townships that have at least one river passing through. Then, using each monitoring station as a center, we draw a circle with a 10-km radius and keep only those townships overlap with a 10-km circle. All the geocoded firms lying in those remaining townships constitute our sample for analysis.

After identifying the relevant firms for our research design, we calculate each firm's distance to its nearest monitoring station. In some cases (mostly in the eastern coastal areas), the distribution of monitoring stations can be very dense. As a result, some 10-km circles overlap with each other, making it difficult to define upstream and downstream relationships (i.e., an adjacent upstream firm for one monitoring station can also be in the near downstream of another monitoring station). We therefore exclude these overlapping monitoring stations from our dataset. In some less-developed regions (mainly in the western areas), the distribution of large industrial firms is so sparse that the 10-km circles around monitoring stations contain no firms from the ASIF and ESR datasets. We also drop these monitoring stations from our sample. After these exclusions, we are left with 161 state-controlled water quality monitoring stations that satisfy our empirical setting. The geographic distribution of these monitoring stations is plotted in Figure III.

For each firm kept in the sample, we project its location onto the nearest river basin and extract the elevation of that projected point. Then, we compare this elevation to the elevation of the adjacent monitoring station, so that we can determine whether each firm is upstream or downstream of the corresponding monitoring station. In the end, our sample includes 17,726 unique ASIF firms and 9,797 ESR firms from 544 townships, located around 161 water quality monitoring stations.

We attempted to match the firms across the ASIF and ESR samples. However, because these two datasets use different sampling criteria and are managed by different government agencies (using different coding systems), we were able to match only 10% of the ASIF firms with the ESR firms. The matched sample is too small for us to draw any credible statistical inference. Therefore, in this paper, we analyze these two datasets separately.

C. Summary Statistics and Balance Checks

The underlying assumption for our spatial RD design is that, in the absence of environmental regulation, upstream and downstream firms should be *ex-ante* identical. We provide a series of balance checks in the appendix, documenting that upstream and downstream firms/townships are similar along time-invariant and pre-determined dimensions, as well as along time-variant dimensions before water quality regulation became effective in 2003.

In Appendix Table S3, we present the summary statistics and balance checks for firm-level characteristics. In the ASIF dataset, the only three (arguably) time-invariant variables are "when the firm was established," "whether the firm is a state-owned firm," and "whether the firm is a polluting firm." As shown in Panel A, all these variables are well balanced around monitoring stations. In addition, surface water regulation was not strictly enforced until President Hu Jintao came into power in 2003; thus, water monitoring stations should not affect upstream firms in the pre-2003 period of our data.[18] In Panel B of Appendix Table S3, we compare upstream firms with downstream firms using pre-2003 data. Again, we find that all the key variables, such as TFP, profit, value-added, employment, capital, and intermediate input, are all well-balanced between upstream and downstream firms before 2003.

In Appendix Table S4, we further test whether different industries are balanced across the monitoring stations. We focus on 2-digit level industries and conduct the balance tests using relatively large industries (with at least 100 firms in the sample in 2000). We find that different industries are equally distributed across the monitoring stations.

In addition to the balance tests using firm-level data, we also conduct balance tests using township-level data and report our findings in Appendix Table S5. In Panel A, we see that basic township time-invariant characteristics are balanced, including township area, arable area, distance to county center, whether the township is an old-region town, whether it is an ethnic minority town, the number of residents, and the number of administrative villages.[19] In Panels B and C, we look at pre-2003 township data and test the balance in basic infrastructure and human capital. Again, we find that the length of roads, number of villages with road access, number of villages with electricity access, number of villages with tap water access, and the number of primary schools and students were similar between upstream and downstream areas before water regulation became a binding constraint.

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[18] The dynamic analysis of the RD results will be discussed in Section V.

[19] An old region refers to a Communist Party revolutionary base region. An administrative village is organized by one village committee and may include several natural villages.

The results in Appendix Tables S3–S5 are encouraging, as they indicate that upstream and downstream firms are similar for both time-invariant characteristics and pre-2003 covariates, and these firms are located in townships that are highly comparable. While it is impossible to completely exhaust the potential unobservable differences between upstream and downstream firms, these balance results lend additional credibility to our research design.[20]

IV. Baseline Results

A. Effects of Water Quality Monitoring on TFP

We begin the empirical analysis by visualizing our main findings. Figure IV plots log TFP (absorbing station FE and industry FE) against "distance to the corresponding monitoring station." Each dot represents the average log TFP for firms within a bin of distance; their 90% confidence intervals are also presented. A fitted curve is then overlaid on the graph to illustrate the discontinuity around the monitoring stations.

In Panel A, we show the RD plot for residual log TFP in the polluting industries. We see a sharp change in TFP at precisely the locations of the water monitoring stations. The TFP of upstream firms is significantly lower than that of downstream firms in polluting industries. Moreover, as can be seen from Panel A, the treatment effect applies only to firms in the immediate upstream (<5km) and becomes stronger as firms locate closer to the monitoring stations. These two patterns correspond to the fact that surface water pollution tends to dissipate over space, so emissions from farther upstream have smaller impacts on water quality readings. Therefore, local officials have little incentive to regulate firms that are farther upstream, if their goal is just to improve the water monitoring readings for political promotion. In contrast, in Panel B, we do not observe any comparable spatial discontinuity in TFP in non-polluting industries.

Table I quantifies the graphical findings in Figure IV. Panel A presents the RD estimates without any controls, for both polluting and non-polluting industries. We see that polluting firms located in the near downstream of monitoring stations have substantially higher TFP than their near upstream counterparts, and there is no similar pattern for non-polluting firms. However, due to large standard errors, the TFP gap in polluting industries is not statistically significant, despite being sizable in magnitude.

Our sample covers 161 water quality monitoring stations in 34 manufacturing industries. A non-saturated RD regression, as reported in Panel A, would compare upstream and downstream firms from

[20] In Appendix Table S6, we also report the summary statistics for the other variables used in the paper.

different clusters (monitoring stations) and industries, introducing substantial noise into the statistical inference.

To address this issue, we control for both station and industry fixed effects in Panel B. By doing so, we effectively compare the TFP differences station by station and industry by industry and then average the differences across stations and industries. Comparing the RD estimates in Panel B to Panel A, we see that the magnitudes of the estimated impacts are quantitatively similar across these two specifications. This is important because it implies that station- and industry-specific characteristics, while important determinants of firm TFP, are uncorrelated with the treatment status. As we control for these fixed effects, the RD coefficients become more precisely estimated, and thus become statistically significant.

The estimates in Panel B suggest that upstream polluting firms suffer from a TFP loss in the range of 29% ($e^{-0.34}$-1) to 32% ($e^{-0.38}$-1). In comparison, the estimates for non-polluting industries are always precisely estimated zeros. This finding suggests that our results are indeed driven by environmental regulation, rather than by other potential confounding differences between upstream and downstream areas. For both sets of results, the RD estimates are highly robust to different choices of kernel functions.

In Panel C, we estimate a more saturated model that controls for station-by-industry fixed effects. This specification compares upstream and downstream firms within the same industry that are spatially adjacent to each other, which teases out any confounding differences in industry types between upstream and downstream areas. Our findings hold with this most restrictive specification: in polluting industries, upstream firms suffer from a large and significant drop in TFP as compared to their downstream counterparts, while there exists no such discontinuity in non-polluting industries.

In terms of magnitudes, the estimates in Panel C suggest a TFP loss for upstream polluting firms in the range of 24% ($e^{-0.27}$-1) to 25% ($e^{-0.29}$-1), which is slightly smaller than the estimates in Panel B (29% to 31%), but the difference is not statistically significant. This slight reduction in magnitude in Panel C is most likely driven by attenuation bias in fixed effects models: in the saturated regression for polluting firms, we have less than 6,000 observations and control for more than 2,000 fixed effects, which would substantially decrease the signal-to-noise ratio and bias the point estimate towards zero (Pischke, 2007).[21]

[21] The attenuation bias associated with controlling for "Station FE*Industry FE" would become particularly salient when we use different subsamples for heterogeneity analysis; because the FEs are absorbed before we split the sample, the number of FEs would remain the same for the splitted subsample, while the number of observations would be reduced significantly. Therefore, we choose the model in Panel B (Station FE + Industry FE) as our preferred specification for subsequent heterogeneity analysis.

While a more than 24% change in TFP is certainly substantial, the magnitude is better interpreted in China's specific context. During our sample period, China experienced unparalleled industrial TFP growth: according to Brandt, Van Biesebroeck, and Zhang (2012), who use the same data and the same Olley-Pakes method for TFP estimation, the average TFP growth among the ASIF firms was 14% in 2005. This is confirmed by our own estimation of an 11.5% yearly firm TFP growth between 2003 and 2007. Having these benchmarks in mind, our RD estimates indicate that high-powered environmental regulation in the immediate upstream of monitoring stations effectively stalled firm productivity growth by two years. As will be discussed in the mechanisms section (Section V), this is mostly driven by the fact that upstream polluting firms need to invest extra capital in abatement facilities that do not contribute much to their output.

To make the comparison between polluting and non-polluting industries in Table I more explicit, we adopt two alternative econometric specifications. Specifically, we pool the data for the polluting and non-polluting firms together, and directly estimate the difference between "the TFP gap in polluting industries" and "the TFP gap in non-polluting industries." The first approach is a "difference in discontinuities" model suggested by Grembi, Nannicini, and Troiano (2016) and Giambona and Ribas (2018), which essentially estimates the baseline non-parametric RD model while interacting every term with a dummy variable indicating "polluting industries." As can be seen in Panel A of Appendix Table S7, this alternative model generates results that are highly consistent with the baseline findings.

The second alternative specification is a more conventional Difference-in-Differences (DiD) model, which, for a given radius around the monitoring station, estimates how the "difference in means between upstream and downstream firms" differs across polluting and non-polluting industries. As shown in Panel B of Appendix Table S7, when the bandwidth is set at 2.5 km, the DiD result is consistent with the findings in Table I. However, as we choose larger bandwidths, the DiD coefficient starts to attenuate towards zero. This is consistent with the pattern documented in Figure IV: upstream firms receive increasingly stringent regulatory attention as they move closer to the monitoring station, while firms more than 5 km away from the monitoring station are essentially unaffected.

B. Dynamic Effects

As discussed in the background section (Section II), the political stakes associated with water quality readings changed substantially during our sample period. Specifically, in 2003, President Hu Jintao proposed the "Scientific Outlook of Development" initiative and started to actively address the pressing environmental challenges in China. In the same year, the MEP set explicit water quality goals for each national monitoring station and made water quality improvement a key political task. This is consistent with the observational pattern in Figure I, which shows that China achieved massive improvements in water quality and COD abatement immediately after 2003.

We therefore hypothesize that the TFP gap between upstream and downstream polluters should become salient after 2003. To formally investigate the dynamics of the baseline discontinuity in TFP, in Figure V, we plot the RD estimates separately for each year. We find that the TFP discontinuity for polluting firms was close to zero from 2000 to 2002, and became significantly larger in 2003. The TFP gap persists over the following years and peaks in 2006, which marks the beginning of the 11th Five-Year Plan. The corresponding regression results are summarized in Appendix Table S8. In the same table, we replicate the exercise for non-polluting firms and find that the estimated RD coefficient fluctuates around zero, and is not statistically significant in any year.

The finding that the monitoring effect is close to zero and statistically insignificant prior to 2003 is consistent with the balance tests and further justifies our identifying assumption: in the absence of tighter water quality regulations, upstream and downstream firms around the same water quality monitoring station had similar levels of productivity. The dynamic pattern of the RD coefficients is also reassuring as it helps rule out alternative explanations: to the extent that one thinks the baseline results were driven by certain confounding factors, such factors would have to be specific not only to upstream vs. downstream firms or polluting vs. non-polluting industries, but also to the timing of environmental policies in China during our sample period.

C. Within-Firm Effects

Motivated by the "break in trends" between upstream and downstream polluters in 2003, we adopt an augmented "difference-in-discontinuities" specification, which investigates within-firm changes in TFP before and after the introduction of stringent water monitoring schemes in 2003. Specifically, following Grembi, Nannicini, and Troiano (2016) and Giambona and Ribas (2020), we use a local linear regression approach to estimate the following equation:

$$(2) \quad \overline{TFP_{ijkt}} = \alpha_1 Down_{ijk} + \alpha_2 Dist_{ijk} + \alpha_3 Down_{ijk} \cdot Dist_{ijk} + \alpha_4 Down_{ijk} \cdot Post03_t$$

$$+\alpha_5 Dist_{ijk} \cdot Post03_t + \alpha_6 Down_{ijk} \cdot Dist_{ijk} \cdot Post03_t + \varepsilon_{ijkt}$$

$$s.t. \; -h \leq Dist_{ijk} \leq h$$

where $Post03_t$ is a dummy variable that equals 1 if $t \geq 2003$, and 0 otherwise. $\overline{TFP_{ijkt}}$ is residualized TFP, absorbing firm fixed effects, industry-by-year fixed effects, and station-by-year fixed effects.

The main advantage of this augmented approach is that we can now fully utilize the panel structure of our data and study only within-firm changes in TFP, which allows us to tease out any confounding differences between upstream and downstream firms caused by endogenous locational choices. We also absorb station-by-year fixed effects and industry-by-year fixed effects to further control for location- and industry-specific shocks in each year.

Table II reports the difference-in-discontinuities estimates, with the year 2003 chosen as the (before/after) cutoff. In columns 1-3, we find that upstream polluters experienced a 19% TFP ($e^{-0.21}$-1) loss after water quality regulation became stringent in 2003, as compared to their downstream counterparts. In comparison, as shown in columns 4-6, there is no such break in trends between upstream and downstream non-polluters.

The estimated treatment effect for upstream polluters is slightly smaller than the baseline results presented in Table I, which is likely a result of attenuation bias caused by absorbing a large number of fixed effects when residualizing TFP. Nevertheless, the fact that the attenuated coefficients are only slightly smaller than the baseline coefficients (statistically indistinguishable) suggests that, even if there is selection bias due to endogenous locational choices, such bias could at most account for only a small proportion of the baseline findings.

In Appendix Table S9, we test the “parallel trends” assumption using data from 2000 to 2002. In this subsample, we use either 2002 or 2001 as the (placebo) cutoff year, and find that the estimated differences in discontinuities are close to zero in all specifications. This finding confirms that the spatial discontinuity in TFP between upstream and downstream polluters did not emerge until the introduction of stringent water monitoring in 2003.

D. Threats to Baseline Findings and Robustness Checks

In the previous subsections, we demonstrated that before 2003, upstream and downstream firms were well balanced in both levels and trends. When water quality monitoring became a political priority in 2003, there emerged a TFP gap between upstream and downstream polluting firms, while no such gap is observed among non-polluting firms. The upstream-downstream TFP gap is predominantly driven by the break in trends among existing firms, rather than a change in the composition of firms around the monitoring stations. All these empirical patterns support the validity of our RD design.

In this subsection, we briefly summarize the additional tests that we conducted to further address the potential threats to our baseline findings, with the details presented in Appendix E. Specifically, we show that the baseline RD results are not driven by: (1) the endogenous location of monitoring stations; (2) the sorting of polluting firms; (3) spillover effects between upstream and downstream firms; (4) potential biases in our baseline TFP measure; or (5) specific choices we make in the RD estimation.

First, we address the potential endogenous location of monitoring stations using an instrumental variable (IV) approach. As discussed in Section II, the MEP explicitly required the water monitoring stations to be built upon the existing hydrological network. The hydrological stations were set up between the 1950s and 1970s when China barely had any industrial pollution. Because their locations were chosen based purely on hydrological considerations, one would expect that, except for leading to the establishment of monitoring stations, the existence of a hydrological station alone should have minimal impact on the production and emission behaviors of adjacent firms. Utilizing this "exclusion restriction," we adopt "whether a firm is in the near upstream area of a hydrological station" as the IV for "whether a firm is in the near upstream area of a monitoring station," and estimate a 2SLS model to quantify the impacts of water quality monitoring on TFP. As discussed in Subsection A of Appendix E, our main findings quantitatively go through under this alternative empirical strategy.

Second, we investigate the possibility that polluting firms might systematically sort away from the near upstream of monitoring stations, which creates a selection bias that could potentially confound our baseline results. As shown in Table II, our RD results go through when exploiting only within-firm variation, suggesting that "endogenous sorting" is not the main driving force behind our findings. Nevertheless, to directly examine whether "sorting" indeed exists in our data, we conduct data-driven manipulation tests following Cattaneo, Jansson, and Ma (2018, 2019), which essentially compares the density of polluting firms around the RD cutoff. We find no discontinuity in firm distribution during our sample period, confirming again that "sorting" cannot explain our main findings. The lack of sorting in the short run is most likely due to the fact that the firms in our ASIF dataset are generally large ones, for whom it is difficult, costly, and time-consuming to relocate. Using more recent ASIF data, we do find that "sorting" becomes more evident in the long run. These results are discussed in more detail in Subsection B of Appendix E.

Third, we conduct a placebo test to assess whether potential spillover effects between upstream and downstream firms contribute to our findings in any substantial way. Specifically, we first replace the actual downstream firms with their best matches from the sample of firms that are not in the neighborhood of any monitoring stations, based on the pre-2003 data. We then estimate the discontinuities between "actual upstream firms" and "placebo downstream firms" using the post-2003 data. Since the “placebo downstream firms” and “actual upstream firms” do not locate close to each other, this placebo regression teases out the potential spillover effects that might exist in the baseline regression. As reported in Subsection C of Appendix E, we do not find significant spillover effects between upstream and downstream polluters.

Fourth, we investigate whether our findings could be reflecting potential biases in the TFP measure itself. Specifically, the baseline Olley-Pakes approach assumes a (conditional) monotonic relationship between investment and productivity, which might be violated if firm investments tend to be “lumpy.” To address this issue, we construct a series of alternative TFP measures: (1) we estimate different versions of Olley-Pakes TFP excluding incidents of “zero investments” and “investment spikes,” and controlling for “capital age”; (2) we follow the approach proposed by Ackerberg, Caves, and Frazer (2015) and use “intermediate input” instead of “capital investment” as the proxy variable, since “intermediate input” could hardly be lumpy; and (3) we follow Syverson (2011) and Greenstone et al. (2012) to construct a simple “index TFP” measure, which also does not rely on the monotonic relationship between investment and productivity. As discussed in Subsection D of Appendix E, our baseline findings hold, both qualitatively and quantitatively, for all these alternative TFP measures.

Finally, in Subsection E of Appendix E, we present a series of additional robustness checks, including estimating parametric RD models, bias-correcting the RD estimates following Calonico, Cattaneo, Titiunik (2014), and adopting alternative bandwidth selectors. All the main findings remain quantitatively similar throughout these alternative specifications. We also conduct a placebo test by moving the original monitoring stations upstream or downstream by 5 km, and re-estimate the RD model for these “placebo” monitoring stations. We find that the discontinuity in TFP is only evident around actual monitoring stations rather than these placebo stations.

V. Mechanisms: Firm Responses to Regulation

How do firms respond to tighter water quality regulations? In this section, we examine the channels through which environmental regulation affects firms’ TFP. The theoretical framework that guides our analysis is presented in Appendix A. In this model, firms need to use extra labor and capital to clean up emissions, and the government can enforce tighter environmental regulation by increasing the emission tax. Facing a higher emission tax, firms need to hire more labor and capital for emission abatement, but these extra inputs do not directly contribute to output production. As a result, tighter environmental regulation will lead to a reduction in firms’ TFP.

Following the model, we estimate the impacts of water quality monitoring on several key variables: (1) input and output measures that constitute TFP; (2) emission reduction efforts at both the production and the abatement stages; (3) final emission outcomes.

A. Input and Output

In Table III, we decompose the baseline TFP results by estimating the upstream-downstream gaps in firm outputs and inputs separately. Panel A of Table III reports the results for output-related measures: value-added and profit. Both measures appear to be lower for upstream polluters, although the findings are not statistically significant due to large standard errors.

In Panel B of Table III, we focus on input-related measures: labor, capital, and intermediate input. We find that upstream polluting firms hire more employees and use slightly more intermediate input, but these effects are statistically insignificant. The most salient pattern is that upstream polluting firms, while they do not produce more output than their downstream counterparts, own significantly higher levels of capital assets. These results are consistent with the theoretical prediction that upstream firms invest in additional abatement (non-productive) equipment to cope with tighter environmental regulation.

Motivated by the findings in Panels A and B, we construct alternative (reduced-form) measures of productivity: "labor productivity" defined as value-added per worker, and "capital productivity" defined as value-added per unit of capital asset. As we can see in Panel C of Table III, labor productivity appears to be slightly lower in the upstream but the difference is not statistically significant, while capital productivity is significantly lower in the upstream, by a magnitude of more than 22%. These results are reassuring that our baseline findings reflect a real loss in the firm's efficiency of production (generating less output with more input), rather than being mechanical to specific procedures of TFP construction.

In columns 4 to 6 of Table III, we report the RD estimates using pre-2003 data. As we can see, before environmental regulation became a binding constraint in 2003, there did not exist any significant gap in inputs and outputs between upstream and downstream polluters, which is consistent with the previous finding, presented in Figure V, that the baseline TFP gap only emerged after 2003. To further investigate the break-in trends in inputs and outputs around the 2003 cutoff, we estimate the difference-in-discontinuities model, absorbing firm fixed effects, station-by-year fixed effects, and industry-by-year fixed effects. As shown in Appendix Table S10, the upstream polluters started to own higher amounts of capital assets after 2003, confirming the findings in Table III.

B. Emission Abatement Actions

Polluting firms can generally take two types of actions to reduce their emissions. First, they can change their production process ("changes-in-process"), defined as adjustments in the production process to reduce the amount of pollution generated. For example, polluting firms could simply choose to produce less, or they could replace their production equipment with cleaner and more efficient equipment. Second, they can have "end-of-pipe" interventions, defined as adjustments at the end of the production process to reduce the amount of pollution released into the environment by removing the pollutants that have already been generated. For example, to abate COD discharges at the end of the pipe, firms typically need to install a wastewater treatment system that includes aeration tanks, air flotation devices, and coagulative precipitation tanks.

In Table IV, we utilize detailed information on abatement strategies documented in the firm-level emission dataset and investigate which type of action is being taken by upstream firms to cope with tighter environmental regulation.

First, we test for changes in the production process. In Panel A, we find that the downstream firms' operating time is longer than that of the upstream firms, with the estimated difference being around 200 hours per year. This result implies that, in order to improve water quality readings, firms located in the near upstream of monitoring stations have to reduce their production time by nearly 5% compared to their downstream counterparts. In Panel B, we examine how much freshwater is used as inputs in the production process. Water is an important input for many industries, and more water usage is usually associated with more wastewater discharge and pollutant emissions. We find that upstream firms use substantially less water in their production than downstream firms do, suggesting that they adopt less water-pollution-intensive technologies in production to cope with the tighter regulation.

Second, we test for end-of-pipe interventions. In the ESR database, each polluting plant is required to report how many wastewater treatment facilities the plant has, and its maximum capacity to treat wastewater. In Panels C and D of Table IV, we find that upstream firms have on average one extra set of wastewater treatment systems, which increases their maximum treatment capacity by more than 7,300 tons per day.[22]

The results in Table IV suggest that both "changes-in-process" and "end-of-pipe" adjustments contributed to upstream polluters' efforts to reduce emissions. Combined with the results documented

[22] This set of results should be interpreted with caution because many polluting sources did not provide information on wastewater treatment capacity.

in Table IV, we have a more comprehensive understanding of the channels through which firms cope with tighter regulation: upstream firms install expensive wastewater treatment facilities to abate emissions, use less water-intensive production technologies, and slightly reduce their operating hours. Together, these investments and adjustments lead to a significant reduction in total factor productivity among upstream polluting firms.

C. Emission Abatement Outcomes

The model in Appendix A predicts that tighter environmental regulations will decrease both emission levels and emission intensity (emission per unit of output). In other words, upstream polluting firms are expected not only to reduce total emissions but also to adopt cleaner technologies. This is consistent with the previous findings that upstream firms invest more in both production and abatement technologies. In this section, we formally examine the impacts of water quality monitoring on firm emissions and emission intensity.

We examine eight pollution outcome measures from the ESR dataset: (1) total amount of COD emitted; (2) COD emission intensity (total COD/total output value); (3) total amount of nitrogen ammonia (NH_3-N) emitted; (4) NH_3-N emission intensity (total NH_3-N/total output value); (5) total amount of wastewater discharged; (6) wastewater discharge intensity (total wastewater/total output value); (7) SO_2 emissions; and (8) NO_x emissions.

Table V reports the results. In Panel A, we can see that both COD emissions and COD emission intensity are significantly higher for downstream firms. COD emissions of polluters in the immediate upstream of monitoring stations are 51.8%–56.8% ($e^{-0.73}$-1 to $e^{-0.84}$-1) lower than that of the immediate downstream polluters. When the amount of total output is adjusted, water quality monitoring reduces the COD emission intensity in upstream firms by 46.2%–56.8% ($e^{-0.62}$-1 to $e^{-0.84}$-1). As discussed in more detail in Appendix A, our model predicts that firms with higher emission intensities would respond more strongly to regulation, which suggests that the upstream-downstream emissions gap should be larger among firms with higher emission intensities. In Appendix Table S11, we estimate the RD separately for high-intensity and low-intensity firms and find that the emission reduction is indeed driven by high-emission-intensity firms.

In Panel B of Table V, we examine nitrogen ammonia (NH_3-N) emissions, another water pollution indicator recorded in the ESR database. NH_3-N is a toxic pollutant often found in landfill leachate and industrial wastewater, and is a common pollutant generated by firms in the coking, petrochemical, pharmaceutical, and food industries. It is widely regarded as an important measure of surface water health: high levels of NH_3-N could induce water body eutrophication, which causes algae and other plankton to multiply in water. However, since the national water quality target focused mostly on COD rather than NH_3-N during our study period, the ESR database did not spend as much effort on measuring NH3-N as it did with COD. As a result, nearly half of the sampled firms did not report their NH_3-N emissions in the ESR data. As shown in Panel B, while the estimated coefficients are relatively noisy due to a large amount of missing data, they do consistently suggest that upstream polluters have much lower NH_3-N emission intensity than downstream polluters.

In Panel C, we further examine wastewater discharge. Again, we observe that upstream firms discharge less wastewater, both in absolute levels and in output-adjusted intensity. This is consistent with the findings in Table V that upstream polluters use less freshwater as an input, and also have higher treatment capacities for wastewater.

The ESR database also includes firms that emit large amounts of SO_2 and NO_x. We use these firms to conduct a placebo test. As these air-polluting firms contribute little to COD emissions, we expect that they do not face similar regulations as the water-polluting firms do. In Panel D, we find that there is no significant discontinuity in SO_2 and NO_x emissions across the water quality monitoring stations, confirming that the upstream-downstream gap is unique to water pollution.

A potential caveat of the ESR database is that it only samples the most polluting firms in each county. Given that we focus on a small region around each monitoring station, many of the upstream and downstream firms are located within the same county. This causes a potential selective attrition problem, because upstream firms facing tighter regulation tend to emit less, and are thus less likely to be sampled in the ESR database. If such selection bias exists, our results in Table V will be underestimates, because the upstream firms that abate most of their emissions are no longer included in the sample. Thus, when we evaluate the environmental benefits of water monitoring, the estimates in Table V should be regarded as lower bounds.

To further demonstrate that the tighter regulation faced by upstream firms is driven by the efforts to improve water quality readings, we would like to directly link the "TFP loss among upstream polluters" to their "reduced COD emissions." However, as explained in Section III, we could not directly merge the ESR dataset with the ASIF dataset, which makes us unable to conduct this test.

As an alternative strategy, we collect the water quality readings of all the state-controlled monitoring stations between 2000 and 2007 and estimate the relationship between "TFP loss among upstream polluters" and "water quality improvement" for the corresponding monitoring stations.[23] We estimate a Difference-in-Differences-in-Differences (DDD) model, investigating whether monitoring stations

[23] We thank a referee for suggesting this test.

experiencing larger water quality improvements also see larger upstream-downstream TFP gaps in that year. As shown in Appendix Table S12, we find that the upstream-downstream TFP gap is mainly driven by monitoring stations experiencing large improvements in water quality, and this relationship exists only among polluting firms. These findings confirm that the baseline TFP gaps are indeed driven by local officials' efforts to improve water quality readings. If we ignore the noisy nature of the estimated coefficients, these DDD results suggest that to improve the water quality reading of a station by one grade (which reduces digestive cancer rate by 9.7% according to Ebenstein (2012)), the upstream firms within a 4-km radius will need to suffer from an average TFP loss of nearly 27%.

VI. The Political Economy of Regulation Enforcement

The empirical analyses in the previous sections show that, due to the political stakes associated with water quality readings, local government officials impose tighter environmental regulations on polluting firms located in the near upstream of national monitoring stations, as compared to their near downstream counterparts. These findings are supported by abundant qualitative evidence summarized in Appendix D, in which we review numerous policy documents from both the central and local governments in China, and demonstrate that "improving water quality readings" is indeed a central component of China's environmental regulation plans. In addition, various levels of local governments have strong political incentives to interfere with firms' production in order to meet the centrally designated water quality targets.

To better understand the political economy of regulation enforcement in China, in this section, we conduct a series of additional empirical analysis. In Subsection A, we present three pieces of evidence showing that the political incentives of local politicians are indeed the driving forces behind our main findings. In Subsection B, we investigate how the regulatory burdens are shared among different types of firms, which shed further light on the incentives of local government officials.

A. Political Economy of Regulation Enforcement

In Panel A of Table VI, we provide evidence that local governments hold double standards in environmental regulation for upstream vs. downstream firms. In the ASIF dataset, we have information on the waste discharge fees paid by each firm in 2004. If the government imposes a "fair" rule of punishing upstream and downstream firms for emissions, we should expect downstream firms to pay more than upstream firms, due to their higher emission levels (as documented in Table V). However, we find that upstream firms need to pay significantly more waste discharge fees to the government. That implies, local governments are able to charge firms at differentiated emission fee rates, even though these firms are located close to each other and are within the same administrative jurisdiction. In practice, Chinese local governments primarily rely on command-and-control type approaches to regulate emissions, and the emission fees *per se* only account for a small proportion of the regulatory burdens faced by polluters. Nevertheless, the fact that the local governments do hold clear double standards even for this second-order policy instrument is indicative that upstream polluters might be assigned "higher bars" in other forms of regulation as well.

In Panel B of Table VI, we examine how the political promotion incentives of local officials drive the upstream-downstream TFP gap. As documented in the Chinese political meritocracy literature, China has an implicit rule that a prefecture-level leader cannot be promoted to a higher level if his/her age reaches 57, creating a discontinuous drop in political incentives at this age cutoff (Wang, 2016). To test whether the TFP effects of water quality monitoring can be explained by political incentives, we digitize the résumés of every prefectural party secretary (the highest-ranked political leader in a prefectural city) between 2000 and 2007, and define a leader as "having strong political incentives" if he/she is younger than 56 in a given year, and "having weak political incentives" otherwise. We then assign a monitoring station either to an "incentivized" or "un-incentivized" party secretary in a given year, based on whether the monitoring station is under the governance of an "incentivized" leader in a particular year. The RD results show that when the prefectural city leader has strong political incentives, water quality monitoring has a large and statistically significant impact on upstream firms' TFP. In sharp contrast, when the prefectural city leader has weak promotion incentives, the TFP gap appears small and insignificant. These results imply that the TFP discontinuity across the monitoring stations is mostly driven by the political promotion incentives of local officials.[24]

Finally, we investigate how the manipulation of water quality readings by politicians affects the enforcement of environmental regulation. Although the monitoring stations are managed by the central government, it is still possible that local officials can exert their administrative powers to influence water quality monitoring. If local governments can manipulate water quality readings, they may be less incentivized to regulate upstream firms' emissions.

To test this hypothesis, we estimate the RD separately for two types of monitoring stations: automatic stations and manual stations. Automatic stations conduct all water quality tests automatically and report the data directly to the central government, while manual stations require

[24] As an alternative way to check this result, we use the panel dataset and exploit the age change from 56 to 57, holding the leader fixed. The main results still hold with this more restrictive specification, as shown in Appendix Table S13.

technicians to conduct the tests manually.[25] Because it is difficult for local governments to manipulate data from the automatic stations, we expect a larger TFP gap around automatic stations.

Panel C of Table VI reports the findings: while we see an upstream-downstream TFP gap for both types of stations, this effect is significantly larger for automatic stations. These results confirm that potential data manipulation undermines the enforcement of environmental regulation, but the agency problem can be alleviated through improved monitoring technologies.

B. Regulatory Burden on Different Types of Firms

This subsection explores whether the effect of water quality monitoring on TFP varies by ownership, firm size, and firm location, which help us understand how different types of firms share the regulatory burdens.

In Panel A of Table VII, we estimate the RD by firm ownership and find that the baseline TFP loss is driven mainly by private firms. Water quality monitoring has no significant impact on the TFP of state-owned enterprises (SOEs). This may reflect the fact that environmental regulations are not binding for SOEs as a practical matter, as they generally have greater bargaining power over local governments and thus face less stringent enforcement. However, given the relatively small number of observations for SOEs in our sample, this sub-sample null result should be interpreted with caution.

In Panel B of Table VII, we investigate heterogeneity by firm size. In China, various levels of government practice a strategy known as "Grasping the Large and Letting Go of the Small" ("*Zhua Da Fang Xiao*"). "Grasping the large" means that policymakers mainly target large enterprises, while "letting go of the small" means that the government exerts less control over smaller enterprises. The phenomenon has been widely documented in the context of economic reforms and policy implementation for the minimization of implementation costs (e.g., Hsieh and Song, 2015). We investigate whether this phenomenon is true in environmental regulation. We define small firms as having fewer than 50 employees and estimate the effects of water quality monitoring separately for small and large firms. We find statistically significant effects only on larger firms, which is consistent with the general policy enforcement strategy adopted by Chinese local governments.

In Panel C of Table VII, we explore regional heterogeneity. Here, we focus on China's South-to-North Water Diversion project. The project is a large-scale water infrastructure project that diverts water from the Yangtze River in southern China to the Yellow River Basin in arid northern China, in

[25] Most stations were manual in the 1990s and early 2000s, but these were gradually replaced by automatic stations in order to improve the accuracy of water quality reporting. Weekly water quality reports from the automatic stations are posted by the MEP at http://datacenter.mep.gov.cn/index and real-time water quality readings can be accessed at http://online.watertest.com.cn/help.aspx.

an attempt to address water scarcity in the north.[26] To do so, the central government imposed stringent requirements that the affected regions must ensure good water quality along the channeled river basins, which adds additional political stakes for the corresponding local governments. We thus split our sample into two sub-regions based on whether the location is designated as the water diversion project region. Our results show that the impact of water quality monitoring on firm productivity is indeed slightly larger in areas that are affected by the project.

VII. Economic Significance

According to our baseline RD estimates, polluting firms located in the immediate upstream of water monitoring stations experienced a TFP loss of more than 24%. A simple within-sample calculation suggests that during our sample period, these upstream polluters jointly sacrificed around 20 billion Chinese yuan in terms of industrial value-added.[27] From 2000 to 2007, China reduced its annual industrial COD emissions by nearly 2 million tons (or 27.6%, as shown in Figure I). This reduction was contributed jointly by firms in our RD sample and many other firms that were further away from the monitoring stations. As a result, a calculation restricted to immediate upstream polluters would capture only a small proportion of the overall economic cost of water regulation in China.

To paint a more comprehensive picture of the aggregate economic cost of abating water pollution, we provide alternative calculations under different scenarios and discuss their implications. First, in Subsection A, we utilize our RD coefficients for out-of-sample calculations, and estimate the overall economic cost associated with China's total reduction in industrial COD emissions. Then, in Subsection B, we discuss the persistence of this aggregate abatement cost. Finally, in Subsection C, we evaluate the potential sources of bias in our calculation.

A. Estimated Loss in Value-Added from Industrial Firms

Our baseline estimates show that, due to tighter water regulation, upstream firms cut their COD emissions by 0.84 logarithmic units, leading to a TFP loss of 0.36 logarithmic units (0.21 if we restrict to within-firm variation). Under several simple functional form assumptions and exploiting the

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[26] The project aims to channel 44.8 billion cubic meters of fresh water annually, which is equivalent to nearly half the amount of water consumed in California annually. For details, please refer to https://www.water-technology.net/projects/south_north/, and https://www.internationalrivers.org/campaigns/south-north-water-transfer-project

[27] If TFP is reduced by x% in a year, the corresponding loss in industrial value-added can be calculated by VA/(1-x%) - VA, where VA is the realized value-added in that year.

sampling criteria of the ASIF and ESR datasets, we can link the two estimates together and obtain the average pollution abatement cost for Chinese manufacturing firms.[28]

In Panel A of Table VIII, we report the estimated TFP loss for a 10% reduction in COD emissions. In columns 1–3, the estimated TFP loss is calculated based on the baseline RD results. We find that abating COD emissions by 10% would lead to a 3.38%–3.81% reduction in TFP. In columns 4-6, the TFP loss is calculated using the more conservative within-firm RD results. A 10% reduction in COD emissions will lead to a 2.12%–2.28% loss in TFP.

In Panel B of Table VIII, we evaluate the economic costs of China's regulations. During our study period (2000-2007), China reduced its total industrial COD emissions by 27.6% (Figure I). Based on the industrial value-added data from the polluting industries in that period, the abatement of COD emissions between 2000 and 2007 would have caused a total loss of 1,342 to 1,527 billion Chinese yuan in industrial value-added if firms were allowed to operate using 2000 technology.[29] If we use the more conservative within-firm estimates (Table II), the estimated cost would still be around 816 to 882 billion Chinese yuan, as reported in columns 4 to 6 in Panel B.

While our data do not allow us to directly estimate the TFP-COD relationship after 2007, we could use the pre-2007 coefficients to shed some light on China's more recent regulatory efforts, assuming that China's industrial structures and regulatory enforcement practices are relatively stable over time. Panel C of Table VIII summarizes our estimates during 2016 and 2020. In 2015, the industrial value-added in China exceeded 23 trillion Chinese yuan, 39% of which was contributed by the polluting industries. The central government aimed to reduce COD emissions by 10% during the 13th Five-Year Plan (2016 to 2020). Applying our estimates to the production data and using 2015 as the reference year, we find that the 5-year total loss in valued-added would be 1,303 to 1,472 billion Chinese yuan. Using the more conservative RD estimates yields smaller estimated economic costs, ranging from 808 to 872 billion Chinese yuan, as reported in columns 4–6 in Panel C.

B. Persistence of the Economic Cost of Regulation

As shown in Section VI, to cope with tighter regulatory standards, upstream polluters invest significantly more in cleaner production and abatement equipment, which is the main driving force behind the upstream-downstream gap in TFP. Since capital stocks depreciate by only a low rate from year to year, the regulation-induced spikes in capital stocks would likely have long-lasting impacts on

[28] The technical details for linking the TFP and COD estimates are discussed in Appendix F.
[29] The total COD reduction is calculated by assuming the 2000 COD emission level as the "counterfactual" for the 2000-2007 period. An alternative approach is to focus on the post-2003 period, and construct the counterfactual by extrapolating based on the pre-2003 trend in COD emissions. We discuss this alternative procedure in detail in Appendix F.

firm productivity. This is confirmed by the dynamics of TFP during our sample period, as documented in Figure 5: the upstream-downstream gap in TFP emerged after water regulation became stringent in 2003, and persisted throughout our sample period.

After 2007, the AISF dataset no longer collected information on firm value-added, so we are unable to track TFP dynamics in the longer run. However, since the “upstream-downstream gap in capital stocks” is the main driving force behind the “upstream-downstream gap in TFP,” we can shed light on the persistence of regulatory costs by investigating the persistence of the capital gap. Specifically, we use 2008 to 2012 ASIF data (the most recent data available to us) and estimate spatial discontinuity in capital stocks. As summarized in Appendix Table S14, we find that the difference in capital stocks between upstream and downstream firms became even larger in the longer term, which could reflect the reality that China’ environmental regulation has becoming more stringent in recent years.

C. Potential Sources of Bias

There are several reasons why the estimates in Table VIII may understate the actual economic costs of China’s water pollution controls. First, we cannot observe small firms in either dataset. In reality, small firms might be shut down by the government to improve water quality readings. The corresponding TFP loss cannot be captured in our estimation and will make our calculation an underestimate of the overall economic cost due to regulation.

Second, the distinction between polluting and non-polluting industries is based on two- to three-digit industrial codes. This distinction does not rule out the possibility that some firms in the non-polluting industries may also emit pollutants and are therefore regulated by local governments. If this is the case, the estimated economic cost will be understated.

Third, we only compute the direct economic costs caused by TFP loss. Previous research has shown that tighter environmental regulation can also cause unemployment, firm relocation, and worker migration, and can change the flow of investment. These indirect costs could contribute to the overall economic costs of environmental regulation in non-trivial ways.

VIII. Conclusion

China, like many other developing economies, faces a stark tradeoff between preserving basic environmental quality and sustaining robust economic growth. This paper is the first to rigorously quantify the impacts of environmental regulation on China’s entire manufacturing sector, which provides a timely assessment of the central government’s efforts in leveraging high-powered political incentives to fight pollution.

We document that, since water quality readings of state-controlled monitoring stations are important for political promotion and can only reflect emissions from upstream, local government officials have strong incentives to regulate polluting firms in the near upstream of monitoring stations, but not those in the near downstream.

Exploiting this spatial discontinuity in regulation stringency embedded in China's target-based regulation enforcement scheme, we estimate that polluting firms in the immediate upstream of monitoring stations suffer a 24% loss in TFP, as compared to their immediate downstream counterparts. This upstream-downstream gap in TFP exists only in polluting industries and did not emerge until water quality readings became a political priority in 2003. Further analysis suggests that the productivity loss is mainly driven by upstream polluters investing more in (non-productive) abatement equipment to cope with tighter regulation, and cannot be explained by the endogenous locations of monitoring stations or polluting firms.

We also investigate the impacts of water quality monitoring on pollution. Using a firm-level emissions dataset, we find that upstream polluting firms emit substantially less COD, NH_3-N, and industrial wastewater, as measured by both absolute emission levels and output-adjusted emission intensities. We also find evidence that upstream polluters cope with tighter regulation by both adjusting the production process and abating "end-of-pipe" emissions.

Combining the RD estimates for TFP and emissions, we calculate the overall economic cost of China's water pollution control policies. We estimate that a 10% abatement in COD emissions can lead to a 3.38%–3.81% drop in TFP for China's polluting industries. This estimated abatement cost implies that China's efforts in reducing COD emissions during our study period (2000 to 2007) led to a total loss in industrial output of more than 800 billion Chinese yuan.

Our paper also sheds light on a more fundamental issue with centralized political regimes. Under political centralization, when the central government wants to mobilize local governments for decentralized policy implementation, it often adopts a target-based incentive scheme where political rewards are promised contingent on meeting certain performance criteria. However, if the central government is unable to perfectly monitor all aspects of decentralized program enforcement, local government officials will exert efforts on the "contractable dimensions" while shirking on the "non-contractable dimensions." As a result, even well-intended central programs could lead to unexpected consequences under decentralized enforcement. In our context, the central government leverages high-powered political incentives to improve surface water quality, but can only observe water quality readings of the state-controlled monitoring stations, which reflect emissions from their upstream but not their downstream. Our findings suggest that local government officials respond strongly to this incomplete political contract by imposing significantly tighter regulation on upstream firms.

Further analysis suggests that political incentives are indeed central to China's environmental regulation enforcement. We first summarize a large body of qualitative policy documents, which demonstrate that "regulating polluting firms to improve water quality readings" was indeed a political priority during our study period. Quantitatively, we document that: (1) local government officials charge higher emissions fees for upstream firms while these firms actually emit less; (2) local officials who stand a chance of being promoted to the provincial level have substantially stronger incentives to regulate upstream firms; and (3) local officials spend more efforts to regulate upstream firms when it becomes harder to directly manipulate the water quality readings. These findings consistently suggest that, under China's target-based regulation enforcement scheme, politically motivated local officials deviate from the central government's intention, by prioritizing "water quality readings" over "actual water quality." Taking into account the political incentives in decentralized regulatory enforcement could be critical in the design of more efficient future regulation programs.

Finally, we point out some limitations of our study and discuss directions for future research. First, our findings cannot fully address the broader question of whether China's current environmental regulations are too aggressive or too lenient, as we have little knowledge about Chinese people's willingness to pay for cleaner surface water.[30] Second, our sample covers a relatively short period of time, while firms might be able to better adjust investment and production in the longer run. With the growing availability of firm-level longitudinal data, investigating how firms respond to regulation over long periods of time will be an important area for future research. Third, given that the current target-based regulation scheme is susceptible to distortions under decentralized enforcement, the feasibility and cost-effectiveness of alternative market-based policy instruments (e.g., cap-and-trade markets) are of obvious importance for policy-making.

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[30] Some studies investigate the health consequences of water pollution in China (e.g., Ebenstein, 2012; He and Perloff, 2016). An omnibus measure of the benefits from improved water quality is still needed, because pollution also decreases recreation, amenity, and many other types of values that people derive from visiting surface waters.

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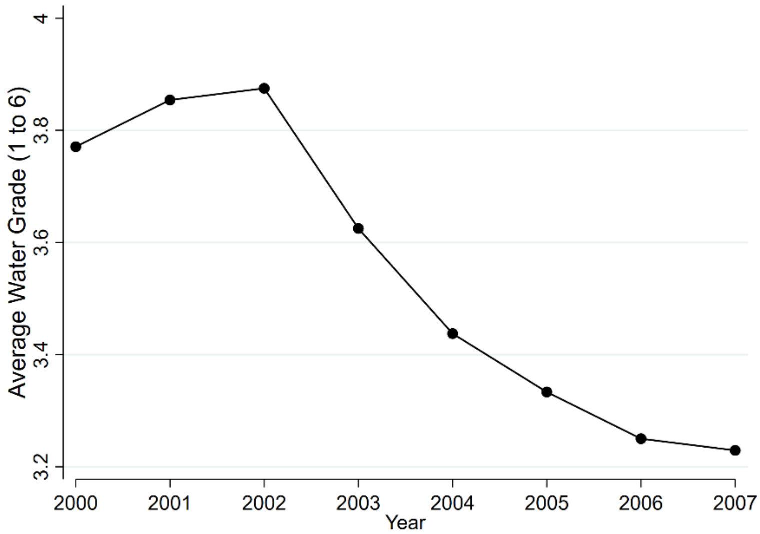
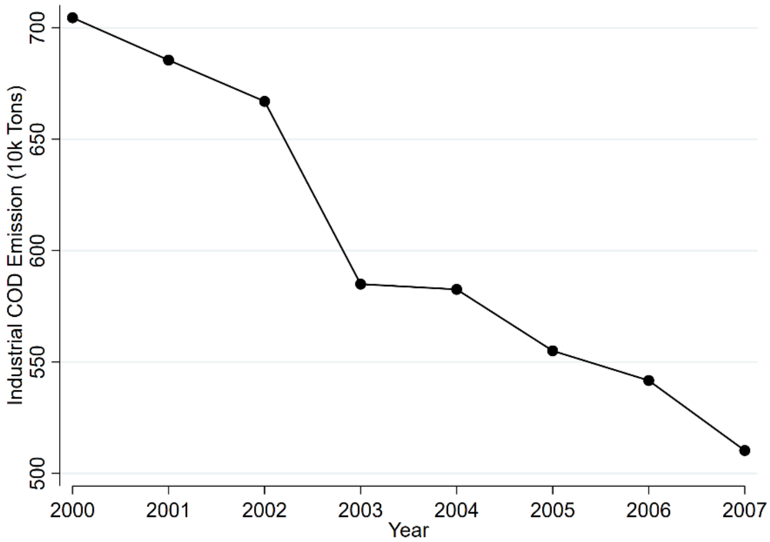
Figure I. Water Quality and COD Emission



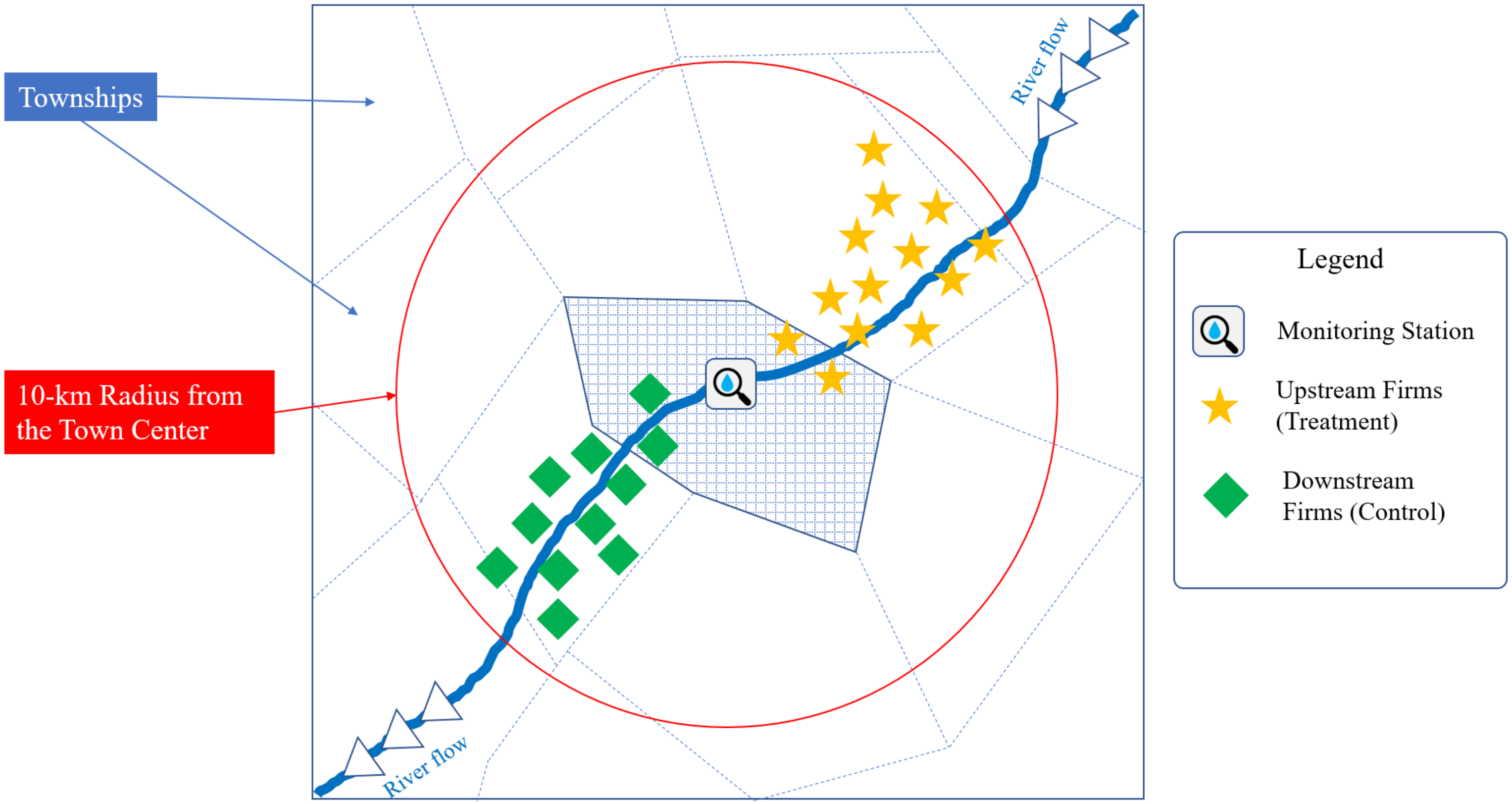
Panel A. Water Quality from 2000 to 2007



Panel B. Industrial COD Emissions from 2000 to 2007

Notes: This figure illustrates the dynamics of water pollution in China. Panel A shows the trend of average water quality readings of national monitoring stations, where 1 represents highest water quality, 6 represents lowest water quality. Panel B shows the trend of national industrial COD emissions.

Figure II. Illustrating the Identification Strategy



Notes: This figure illustrates our identification strategy. We compare firms located immediately upstream of a monitoring station to those located immediately downstream of a monitoring station.

Figure III. Distribution of Surface Water Quality Monitoring Stations in China

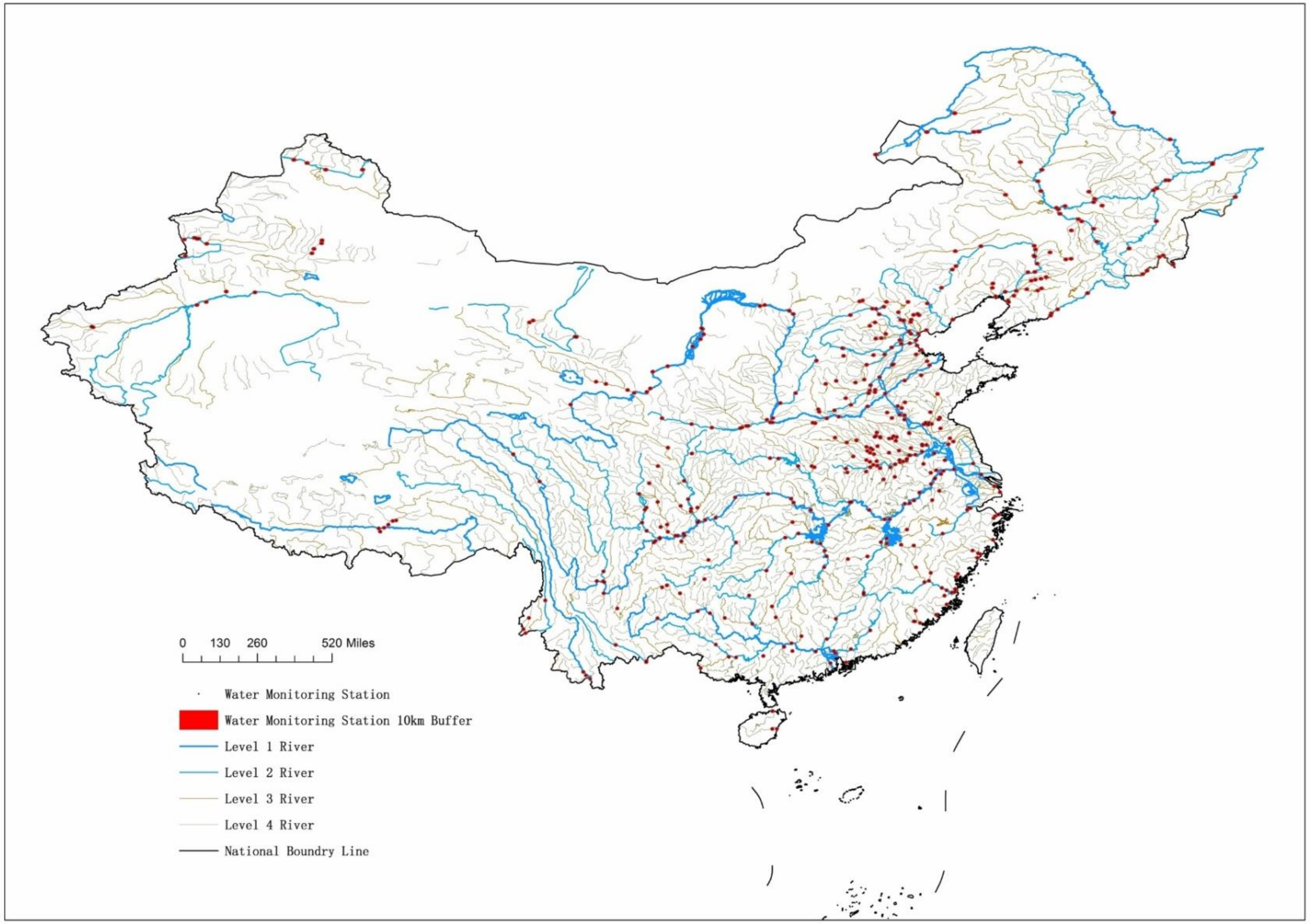
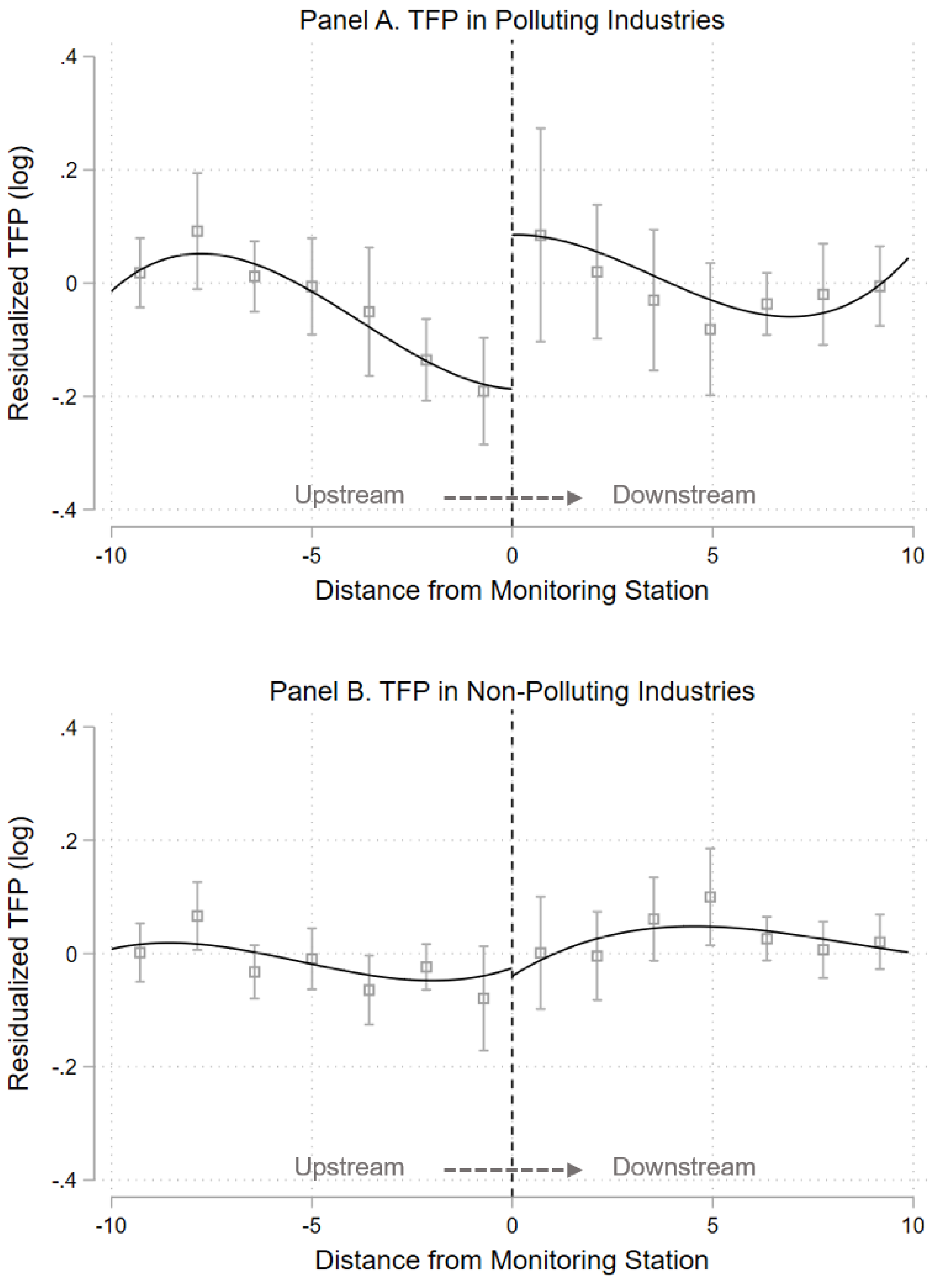
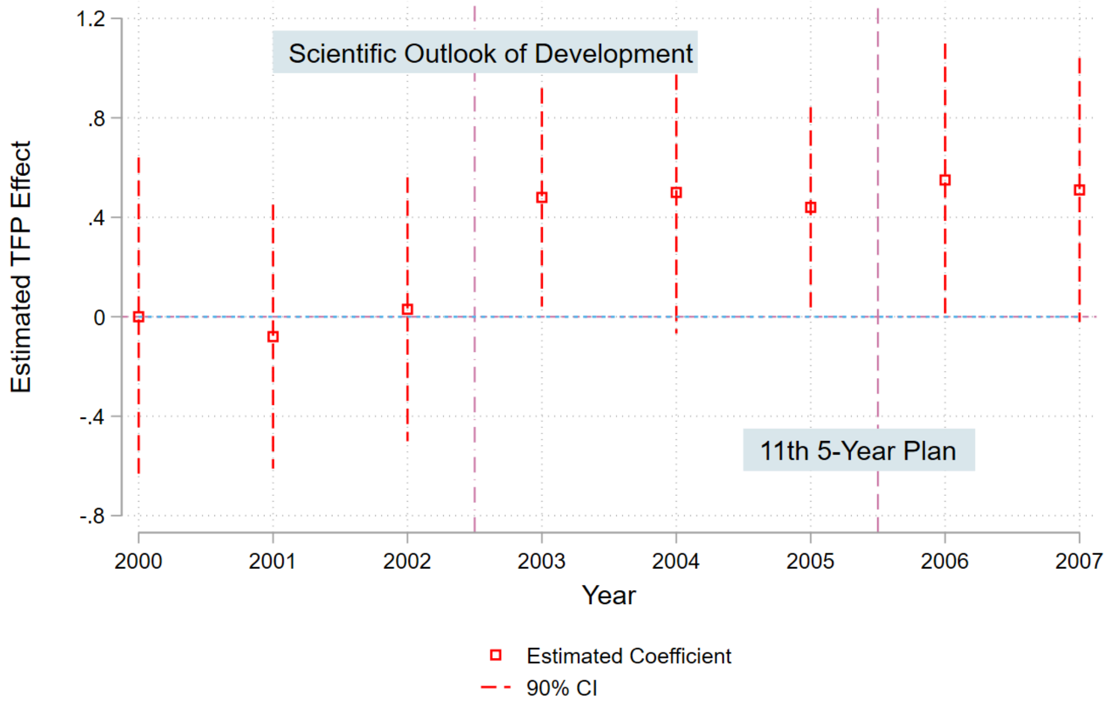


Figure IV. RD Plot: Effects of Water Quality Monitoring on TFP



Notes: Industry and monitoring station fixed effects are absorbed before plotting the regression discontinuities.

Figure V. RD Estimates by Year



Notes: Each dot represents a separate RD estimate in Table I. Industry and monitoring station fixed effects are absorbed before estimating the discontinuities in each year. This figure shows that the TFP discontinuity around monitoring stations for polluting firms became larger and statistically significant after 2003.

Table I. The Upstream-Downstream TFP Gap

	Polluting Industries			Non-Polluting Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: No Control						
RD in TFP (log)	0.34	0.37	0.32	-0.03	0.04	0.01
(Downstream - Upstream)	(0.57)	(0.59)	(0.56)	(0.15)	(0.18)	(0.18)
Bandwidth (km)	4.203	3.889	3.622	5.887	5.168	4.522
Panel B: Station FE + Industry FE Absorbed						
RD in TFP (log)	0.36**	0.38**	0.34**	0.03	0.04	-0.02
(Downstream - Upstream)	(0.17)	(0.17)	(0.15)	(0.09)	(0.09)	(0.09)
Bandwidth (km)	5.723	5.523	5.144	5.890	5.479	6.091
Panel C: Station by Industry FE Absorbed						
RD in TFP (log)	0.27*	0.29**	0.29**	0.02	0.04	0.03
(Downstream - Upstream)	(0.15)	(0.15)	(0.14)	(0.06)	(0.06)	(0.07)
Bandwidth (km)	4.496	4.333	4.689	5.692	5.204	4.430
Obs.	6,224	6,224	6,224	11,502	11,502	11,502
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher TFP than upstream firms. TFP is estimated using the Olley and Pakes (1996) method, with "upstream polluting" added as an additional state variable. The discontinuities at monitoring stations are estimated using local linear regressions and MSE-optimal bandwidth proposed by Calonico, Cattaneo, Titiunik (2014) for different kernel weighting methods. Standard errors clustered at the monitoring station level are reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Table II.The Upstream-Downstream TFP Gap: Difference in Discontinuities Estimates

	Polluting Industries			Non-Polluting Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream*Post2003	0.21***	0.21***	0.20***	0.03	0.01	-0.06
	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)
Firm FE Absorbed	Yes	Yes	Yes	Yes	Yes	Yes
Station-by-Year FE Absorbed	Yes	Yes	Yes	Yes	Yes	Yes
Industry-by-Year FE Absorbed	Yes	Yes	Yes	Yes	Yes	Yes
Sample	00-07	00-07	00-07	00-07	00-07	00-07
Bandwidth (km)	6.235	5.880	5.322	6.346	6.273	6.346
Obs.	20,588	20,588	20,588	34,892	34,892	34,892
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate "difference in discontinuities" estimate: the difference between "TFP discontinuity before 2003" and "TFP discontinuity after 2003." The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher TFP than upstream firms. TFP is estimated using the Olley and Pakes (1996) method, with "upstream polluting" added as an additional state variable. The fixed effects are pre-absorved by TFP through an OLS regression. The discontinuities at monitoring stations are estimated using local linear regressions and MSE-optimal bandwidth proposed by Calonico, Cattaneo, Titiunik (2014) for different kernel weighting methods. Bias-corrected coefficients are reported. Firm fixed effects, station-by-year fixed effects, and industry-by-year fixed effects are absorbed before estimating the discontinuities. * significant at 10% ** significant at 5% *** significant at 1%.

Table III. The Upstream-Downstream Gap in Input and Output Levels

	After 2003			Before 2003		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Output Levels (Downstream minus Upstream)						
RD in Profit (10k RMB)	478.59	441.18	693.76	-207.19	-233.60	250.92
	(470.49)	(524.34)	(595.49)	(386.84)	(410.51)	(494.19)
RD in Value-Added (log)	0.05	0.07	0.11	-0.11	-0.09	0.03
	(0.19)	(0.19)	(0.18)	(0.13)	(0.14)	(0.16)
Panel B. Input Levels (Downstream minus Upstream)						
RD in # of Employees (log)	-0.22	-0.19	-0.09	-0.07	0.01	0.05
	(0.16)	(0.16)	(0.16)	(0.19)	(0.19)	(0.20)
RD in Capital Stock (log)	-0.40*	-0.45*	-0.61**	-0.06	-0.04	-0.04
	(0.22)	(0.27)	(0.29)	(0.21)	(0.22)	(0.26)
RD in Intermediate Input (log)	-0.05	-0.04	-0.05	-0.03	-0.01	0.05
	(0.24)	(0.24)	(0.18)	(0.16)	(0.16)	(0.20)
Panel C. Single Factor Productivity (Downstream minus Upstream)						
RD in (VA/Employee) (log)	0.08	0.08	0.05	0.00	0.02	0.01
	(0.08)	(0.08)	(0.08)	(0.06)	(0.06)	(0.05)
RD in (VA/Capital Stock) (log)	0.25**	0.27***	0.28***	0.04	0.04	-0.00
	(0.10)	(0.10)	(0.10)	(0.08)	(0.09)	(0.10)
Obs.	5,520	5,520	5,520	2,282	2,282	2,282
Station FE Absorbed	Y	Y	Y	Y	Y	Y
Industry FE Absorbed	Y	Y	Y	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher "Y" than upstream firms. In columns 1-3, we report the estimated discontinuities for polluting industries using pre-2003 data, and in columns 4-6, we report the estimated discontinuities for polluting-industries using post-2003 data. Local linear regression and MSE-optimal bandwidth proposed by Calonico, Cattaneo, Titiunik (2014) for different kernel weighting methods are used for the estimation. Standard errors are clustered at the monitoring station level and reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Table IV. The Upstream-Downstream Gap in Abatement Efforts

	(1)	(2)	(3)
Panel A: Hours Operated per Year (Downstream minus Upstream)			
RD in Operating Hours	288***	256**	171*
	(101)	(105)	(92)
Obs.	7,302	7,302	7,302
Panel B: Water Input (Downstream minus Upstream)			
RD in Log (Water Input)	0.62***	0.60**	0.40
	(0.23)	(0.25)	(0.28)
Obs.	6,606	6,606	6,606
Panel C: Wastewater Treatment Facility (Downstream minus Upstream)			
RD in # of Treatment Facilities	-1.15*	-1.07*	-1.29*
	(0.62)	(0.62)	(0.69)
Obs.	7,265	7,265	7,265
Panel D: Treatment Capacity (Downstream minus Upstream)			
RD in Water Treatment Capacity (tons/day)	-7,381**	-8,594**	-7,849**
	(3,733)	(3,855)	(3,714)
Obs.	4,624	4,624	4,624
Station FE Absorbed	Y	Y	Y
Industry FE Absorbed	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher "Y" than upstream firms. The discontinuities at monitoring stations are estimated using local linear regressions and MSE-optimal bandwidth proposed by Calonico, Cattaneo, Titiunik (2014) for different kernel weighting methods. Standard errors clustered at the monitoring station level are reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Table V. The Upstream-Downstream Gap in Emissions

	(1)	(2)	(3)
Panel A: COD Emissions (Downstream minus Upstream)			
RD in COD Emissions (log)	0.84**	0.75*	0.73**
	(0.43)	(0.39)	(0.35)
RD in COD Emission Intensity (log)	0.77***	0.70***	0.84**
	(0.29)	(0.27)	(0.33)
Obs.	9,797	9,797	9,797
Panel B: NH3-N Emissions (Downstream minus Upstream)			
RD in NH3-N Emissions (log)	0.87	0.76	0.46
	(0.90)	(0.76)	(0.62)
RD in NH3-N Emission Intensity (log)	1.23***	1.01**	0.73*
	(0.45)	(0.44)	(0.44)
Obs.	4,772	4,772	4,772
Panel C: Wastewater Discharge (Downstream minus Upstream)			
RD in Waste Water Discharge (log)	0.34	0.33	0.06
	(0.31)	(0.33)	(0.26)
RD in Waste Water Discharge Intensity (log)	0.43**	0.38*	0.56**
	(0.21)	(0.20)	(0.26)
Obs.	9,797	9,797	9,796
Panel D: Air Pollutants for Placebo Tests (Downstream minus Upstream)			
RD in SO2 Emissions (log)	0.03	0.06	-0.16
	(0.29)	(0.30)	(0.25)
RD in NOx Emissions (log)	0.09	0.14	-0.05
	(0.28)	(0.29)	(0.20)
Obs.	4,740	4,740	4,740
Station FE Absorbed	Y	Y	Y
Industry FE Absorbed	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher emissions than upstream firms. Local linear regression and MSE-optimal bandwidth selected by Calonico, Cattaneo, Titiunik (2014) for different kernel weighting methods are used for the estimation. Conventional local linear regression discontinuity standard errors clustered at the monitoring station level are reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Table VI. Political Economy of Water Quality Monitoring

	Polluting Industries			Non-Polluting Industries		
	(1)		(2)	(3)		(4)
Panel A. "Double Standard"						
Waste Discharge Fee (log)	-0.91**	-1.12**	-0.91*	/	/	/
(Downstream minus Upstream)	(0.44)	(0.45)	(0.48)	/	/	/
Obs.	3,050	3,050	3,050			
Panel B. Strong vs. Weak Political Incentives						
TFP (log) - Strong Incentive	0.56***	0.58***	0.59***	0.12	0.09	0.07
(Downstream minus Upstream)	(0.20)	(0.20)	(0.20)	(0.13)	(0.14)	(0.10)
Obs.	5,305	5,305	5,305	9,382	9,382	9,382
TFP (log) - Weak Incentive	0.13	0.19	0.18	0.04	0.01	0.26
(Downstream minus Upstream)	(0.19)	(0.25)	(0.27)	(0.19)	(0.19)	(0.22)
Obs.	2,450	2,450	2,450	4,738	4,738	4,738
Panel C. Automatic vs. Manual Monitoring Stations						
TFP (log) - Automatic Stations	1.18**	1.22**	1.21**	-1.07	-0.48	-0.43
(Downstream minus Upstream)	(0.55)	(0.55)	(0.47)	(1.44)	(0.76)	(0.32)
Obs.	932	932	932	1,815	1,815	1,815
TFP (log) - Manual Stations	0.30**	0.35**	0.41**	0.10	0.11	0.10
(Downstream minus Upstream)	(0.15)	(0.17)	(0.20)	(0.08)	(0.08)	(0.08)
Obs.	4,953	4,953	4,953	9,523	9,523	9,523
Station FE Absorbed	Y	Y	Y	Y	Y	Y
Industry FE Absorbed	Y	Y	Y	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression.The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher "Y" than upstream firms. We focus on polluting firms and use post-2003 collapsed data to estimate the regression discontinuities. Local linear regression and MSE-optimal bandwidth proposed by Calonico, Cattaneo, Titiunik (2014) for different kernel weighting methods are used for the estimation. Panel A examines how tax and waste discharge fee collected by the government differ between upstream and downstream firms. Panel B estimates the discontinuities separately using the subsamples where the Prefecture Party Secretary has or does not have strong promotion incentives (age<=56 vs. age >=56). Panel C estimates the discontinuities separately for automatic and manual monitoring stations. * significant at 10% ** significant at 5% *** significant at 1%.

Table VII. Heterogeneous Impacts of Water Quality Monitoring

	Polluting Industries			Non-Polluting Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: By Ownership						
Private Firms	0.45**	0.48***	0.43***	0.05	0.05	0.07
(Downstream minus Upstream)	(0.18)	(0.18)	(0.17)	(0.09)	(0.09)	(0.10)
Obs.	6,149	6,149	6,149	11,510	11,510	11,510
SOEs	-0.11	0.00	-0.01	0.11	0.09	0.06
(Downstream minus Upstream)	(0.44)	(0.51)	(0.61)	(0.35)	(0.33)	(0.41)
Obs.	513	513	513	1,169	1,169	1,169
Panel B: By Size						
Small Firm (Empl<50)	0.06	0.13	0.17	-0.01	-0.04	0.04
(Downstream minus Upstream)	(0.41)	(0.36)	(0.39)	(0.16)	(0.16)	(0.18)
Obs.	1,829	1,829	1,829	3,981	3,981	3,981
Large Firm	0.49***	0.52***	0.52***	0.02	0.03	0.02
(Downstream minus Upstream)	(0.16)	(0.17)	(0.17)	(0.11)	(0.11)	(0.10)
Obs.	4,818	4,818	4,818	8,765	8,765	8,765
Panel C. by Region: the "South-to-North Water Diversion (SNWD)" Project						
SNWD Region	0.89***	0.69**	0.94***	0.17	0.23	-0.19
(Downstream minus Upstream)	(0.31)	(0.32)	(0.31)	(0.18)	(0.15)	(0.52)
Obs.	933	933	933	1,429	1,429	1,429
Other Regions	0.38**	0.35*	0.36**	0.13	0.11	0.11
(Downstream minus Upstream)	(0.19)	(0.18)	(0.18)	(0.11)	(0.10)	(0.11)
Obs.	4,998	4,998	4,998	9,739	9,739	9,739
Station FE Absorbed	Y	Y	Y	Y	Y	Y
Industry FE Absorbed	Y	Y	Y	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher "Y" than upstream firms. Local linear regression and MSE-optimal bandwidth proposed by Calonico, Cattaneo, Titiunik (2014) for different kernel weighting methods are used for the estimation. Conventional local linear regression discontinuity standard errors clustered at the monitoring station level are reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Table VIII. Economic Costs of COD Abatement

	Cross-Section RD			Within-Firm RD		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. MRS between TFP Loss and COD Reduction						
TFP Loss per 10% COD Emission Abatement	3.38%	3.81%	3.53%	2.12%	2.28%	2.22%
Panel B. Estimated Costs for all Polluting Firms from 2001 to 2007						
Total Loss in Industrial VA from 2001 to 2007 (billion CNY)	1,342	1,527	1,408	816	882	858
Panel C. Estimated Costs for all Polluting Firms during the 13th Five Year Plan						
Annual Loss in VA (For 2% COD Reduction, billion CNY)	261	294	273	162	174	170
Total Loss in Industrial VA in Five Years (For 10% COD Reduction, billion CNY)	1,303	1,472	1,364	808	872	849
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: The cost estimates are based on industrial value-added data reported by the National Bureau of Statistics of China. Panel B uses actual industrial value-added from 2000 to 2007 to calculate the cost, and Panel C uses industrial value-added in 2015 as the reference year to estimate the cost from 2016 to 2020. Details can be found in Appendix F.

Online Appendix
(Not for Publication)

WATERING DOWN ENVIRONMENTAL REGULATION IN CHINA

GUOJUN HE SHAODA WANG BING ZHANG

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Appendix A. Conceptual Framework

In this appendix, we present a simple conceptual framework that helps rationalize the empirical findings. We focus on firms' production decisions and address how environmental regulations can affect their TFP. We assume that firms produce homogeneous goods, with a Hicks-neutral continuously differentiable production function $Q(K,L)$, where K represents capital, L represents labor, and $Q_k, Q_l > 0; Q_{kk}, Q_{ll} < 0$.

When a firm produces output Q, emissions are generated as a by-product and are an increasing function of output Q. The firm can reduce its emissions by employing extra (non-productive) labor L_E and/or capital K_E. The final emission level is therefore a continuously differentiable function $E(Q, K_E, L_E)$. We assume that $E_1 > 0, E_{11} > 0; E_2 > 0, E_{22} < 0; E_3 > 0, E_{33} < 0$ and $E_{23} = E_{32} = 0$.

We model the government's environmental regulations as a unit tax (fine), t, on a firm's emissions E. A firm maximizes its profit by setting K, L, K_E, L_E as follows:

(1) $$\max_{K,L,K_E,L_E} \pi = p \cdot Q(K,L) - r \cdot (K + K_E) - w \cdot (L + L_E) - t \cdot E(Q, K_E, L_E)$$

where p represents the market output price, r represents the capital price or interest rate, and w represents wages.

The first-order conditions for the firm's profit maximization problem are therefore:

(2) $$\frac{\partial \pi}{\partial K} = p \cdot Q_k - r - t \cdot E_1 \cdot Q_k = 0$$

(3) $$\frac{\partial \pi}{\partial L} = p \cdot Q_l - w - t \cdot E_1 \cdot Q_l = 0$$

(4) $$\frac{\partial \pi}{\partial K_E} = -r - t \cdot E_2 = 0$$

(5) $$\frac{\partial \pi}{\partial L_E} = -w - t \cdot E_3 = 0$$

Applying the implicit function theorem, we can prove the following:

(6) $$\frac{\partial K}{\partial t} < 0, \frac{\partial L}{\partial t} < 0; \frac{\partial K_E}{\partial t} > 0, \frac{\partial L_E}{\partial t} > 0;$$

(7) $$\frac{\partial E/\partial t}{E} < \frac{\partial Q/\partial t}{Q} < 0;$$

$$(8) \qquad \frac{\partial Q/\partial t}{Q} < \frac{\partial(K+K_E)/\partial t}{(K+K_E)}; \;\; \frac{\partial Q/\partial t}{Q} < \frac{\partial(L+L_E)/\partial t}{(L+L_E)}.$$

Proposition 1. An increase in the emissions tax increases abatement inputs.

Proof. This follows directly from Equation (6).

Proposition 2. An increase in the emissions tax reduces TFP.

Proof. By definition, TFP $= \frac{p\cdot Q(K,L)}{r\cdot(K+K_E)+w\cdot(L+L_E)}$; and we therefore have the following:

$$(9) \qquad \frac{\partial \mathrm{TFP}}{\partial t} = \frac{\partial[\frac{p\cdot Q(K,L)}{r\cdot(K+K_E)+w\cdot(L+L_E)}]}{\partial t} = p\cdot \frac{r\left[\frac{\partial Q}{\partial t}\cdot(K+K_E)-Q\cdot\frac{\partial(K+K_E)}{\partial t}\right]+w\left[\frac{\partial Q}{\partial t}\cdot(L+L_E)-Q\cdot\frac{\partial(L+L_E)}{\partial t}\right]}{[r\cdot(K+K_E)+w\cdot(L+L_E)]^2} < 0$$

where the inequality follows from Equation (8).[31]

Proposition 3. An increase in the emission tax t reduces the emission level E and emission intensity $\frac{E(Q,K_E,L_E)}{Q}$.

Proof. Taking the derivative of emissions with respect to the emission tax, we have:

$$(10) \qquad \frac{\partial E}{\partial t} = E_1\cdot\frac{\partial Q}{\partial t} + E_2\cdot\frac{\partial K_E}{\partial t} + E_3\cdot\frac{\partial L_E}{\partial t} < 0;$$

where the inequality follows from Equations (6) and (7).

For emission intensity, we have:

$$(11) \qquad \frac{\partial(E/Q)}{\partial t} = \frac{\frac{\partial Q}{\partial t}\cdot Q - \frac{\partial E}{\partial t}\cdot E}{E^2} < 0$$

where the inequality follows from Equation (7).

Extension

We extend the model to generate additional predictions regarding the heterogeneous impacts of environmental regulation.

[31] In this model, we implicitly assume that production has no effect on the market price. This assumption is likely to hold in our empirical setting because we focus on a small set of firms concentrated in a small geographical area. On the one hand, these firms face the same market because they are located close to each other; on the other hand, as there are many other firms and buyers in the market, local water quality regulations cannot affect the output market prices. This is important because we cannot directly measure output quantity Q in our firm-level production data. Instead, we can only measure revenue $p\cdot Q(K,L)$. Because firms are price-takers in our setting, we can translate the effects of environmental regulation on revenue-based TFP to real (output-based) TFP. In the case where prices depend on marginal cost, we will underestimate the true TFP effect because the price increases as marginal cost of production increases.

Assume Cobb-Douglas total emission follows $E = Q^{\delta} f\left(\frac{k}{k_E}, \frac{L}{L_E}\right) = Q^{\delta}\left(\frac{k}{k_E}\right)^{\theta_K}\left(\frac{L}{L_E}\right)^{\theta_L}$, where output $Q = \zeta F(K, L) = \zeta K^{\epsilon_K} L^{\epsilon_L}$. Plugging these expressions into Equation (1) and solving the optimization problem, we get:

$$(12) \qquad \frac{K_E}{K+K_E} = \frac{\frac{\theta_K E}{Q}}{\epsilon_K(\frac{p}{t} - \frac{\delta E}{Q})}; \qquad \frac{L_E}{L+L_E} = \frac{\frac{\theta_L E}{Q}}{\epsilon_L(\frac{p}{t} - \frac{\delta E}{Q})}$$

Proposition 4. Dirtier (those generating more emission per unit of output) firms will have larger reductions in emission intensity.

Proof. From Equation (12), we get:

$$(12) \qquad \frac{K}{K_E} = \frac{\epsilon_K}{\theta_K}\left(\frac{pQ - \delta tE}{tE}\right) - 1; \quad \frac{L}{L_E} = \frac{\epsilon_L}{\theta_L}\left(\frac{pQ - \delta tE}{tE}\right) - 1$$

Without loss of generality, assume $\frac{\theta_K}{\epsilon_K} = \frac{\theta_L}{\epsilon_L} = \alpha$, and $\delta = 1$. Therefore, we have:

$$(13) \qquad \frac{\partial(\frac{K}{K_E})}{\partial \alpha} < 0; \ \frac{\partial(\frac{L}{L_E})}{\partial \alpha} < 0$$

This gives us:

$$(14) \qquad \frac{\partial(\frac{E}{Q})}{\partial \alpha} = f_1 \cdot \frac{\partial\left(\frac{K}{K_E}\right)}{\partial \alpha} + f_2 \cdot \frac{\partial\left(\frac{L}{L_E}\right)}{\partial \alpha} < 0$$

Proposition 5. Dirtier firms (those generating more emission per unit of output) will have larger efficiency losses compared to their productivity frontier.

Proof. Given the Cobb-Douglas form, we have $\frac{K_E}{K} = \frac{L_E}{L} = \beta$, where $\frac{\partial \beta}{\partial \alpha} > 0$

Define "Productivity Frontier ($\overline{TFP}$)" as the TFP that the firm could have achieved, had it not allocated resources to the (non-productive) sectors (K_E, L_E). Efficiency loss can be measured by deviation from the productivity frontier:

$$(15) \qquad \frac{\overline{TFP} - TFP}{\overline{TFP}} = 1 - \frac{rK + wL}{rK\left(1 + \frac{K_E}{K}\right) + wL\left(1 + \frac{L_E}{L}\right)} = \frac{\beta}{1+\beta}$$

Given $\frac{\partial \beta}{\partial \alpha} > 0$, we have:

$$(16) \qquad \frac{\partial(\frac{\overline{TFP} - TFP}{\overline{TFP}})}{\partial \alpha} = \frac{\partial(\frac{\beta}{1+\beta})}{\partial \alpha} > 0.$$

Appendix B. Location Choices of Water Quality Monitoring Stations

When China's water monitoring network was set up in the 1990s, the government's main purpose was to achieve a comprehensive understanding of the country's surface water quality, rather than to rely on the readings for regulatory enforcement. Guided by this principle, the monitoring stations covered all the major rivers, lakes, and reservoirs in China, and were established in a way that was spatially representative of neighboring water bodies to properly reflect changes in water pollutants over time. Consequently, the locations of the monitoring stations were mainly determined by hydrological factors.

In this paper, we focus on the state-controlled surface water quality monitoring stations, which are established and supervised by the MEP and the State Council of China.[32] The water quality readings from these state-controlled stations are reported directly to the MEP to ensure data quality. Yearly average water quality readings from the stations are reported in the environmental yearbooks and used by the central government to assess the environmental performance of local government officials. According to the MEP, the state-controlled monitoring stations should be placed in rivers with steady flows, wide water surfaces, and stable river beds, and should avoid stagnant water areas, backwater areas, sewage outfalls, rapids, and shallow water. According to the "*Technical Specification Requirements for Monitoring of Surface Water and Wastewater*," the state-controlled stations should be established to serve "long-term" and "high-level" purposes, meaning that short-term and specific needs (such as monitoring a specific region or a specific polluter) cannot affect the location choices of state-controlled stations.

Another important feature is that, in the "Technical Specification Requirements for Monitoring of Surface Water and Wastewater," the MEP explicitly required the state-controlled monitoring stations to be built at the same locations as existing hydrological stations whenever possible. The intention of this rule was to combine hydrological parameters with water quality readings, as well as pooling resources and facilities from both stations. Since most of the hydrological stations were built in the 1950s and 1960s for purely hydrological purposes (measuring water depth/speed, soil characteristics of riverbanks, etc.), this "co-location" rule provides variations in the location of monitoring stations that are orthogonal to local production and emission activities. In Section IV (D), we will exploit this

[32] Aside from state-controlled stations, there are also localized stations and special stations designed to monitor the emissions of certain major polluters. The special monitoring stations are placed immediately downstream from the polluter to monitor its environmental performance. We do not have data for these types of stations.

feature in an Instrumental Variable framework to provide additional support for the validity of our research design.

Appendix C. Estimation of TFP using Olley-Pakes Method

The main TFP measure used in this paper is estimated following the control function approach developed by Olley and Pakes (1996). The dataset we use is based on the Annual Survey of Industrial Firms (ASIF) collected by the National Bureau of Statistics (NBS). We use data for all ASIF firms between 2000 and 2007, since after 2007 the dataset no longer includes information on value-added. To assemble the ASIF as a panel dataset and construct the key variables for TFP estimation, we borrow heavily from the procedure elaborated in Brandt et al. (2012). Some minor adjustments are made in the construction and cleaning of key variables, following the suggestions of Yang (2015) and helpful comments we received from the editor and four referees. In this appendix, we explain in detail the key steps in our TFP estimation.

Gross Output

Following the literature, we use production value, instead of sales, as the gross output measure. The production value and sales differ slightly due to the change in inventories. The former is more closely related to input and productivity, and thus more relevant for TFP estimation.

When constructing output deflators, we follow Yang (2015) by using output price indexes for every 2-digit industry in each year from the "Urban Price Yearbook 2011" published by the NBS. Because those price indexes are linked across different years, we can use them to deflate yearly nominal output to real output in 2000.

Value Added

When constructing real value-added, we subtract "goods purchased for resale," "indirect taxes," and "material inputs" from the aforementioned "real output" variable.

We construct input deflators from the National Input-Output tables of 1997, 2002, and 2007, to take into account the dynamics of input price in different sectors, as suggested by Yang (2015). By doing so, we are able to deflate nominal inputs in each sector in each year to the real values in 2000.

Employment and Wages

The ASIF dataset contains information on the number of employees and the compensation for labor, including wages, employee supplementary benefits, and insurance. We follow Brandt et al. (2012) to sum up wages, benefits, and insurance as a proxy for total labor compensation.

Capital Stock and Investment

In the ASIF dataset, firms report the value of their fixed capital stock at original purchase prices, as well as capital stock at the originally purchased prices less accumulated depreciation. Because these values are the sum of nominal values in all the past years, they cannot be taken directly to proxy for real capital stock. To back out the real capital stock and construct real investment from this variable, we follow the approach suggested by Yang (2015).

For each year after the first period, we first take the difference between "current capital stock" and "capital stock in the previous period," then deflate it according to the previously calculated price indexes for this period. For observations in the first period of the panel, we assume that, from the firm's establishment until this first period, it had on average the same increasing trend in investment rate as the 2-digit sector average value, which can be collected from the yearbooks published by the NBS. Under this assumption, together with the nominal capital stock in the first period, nominal capital stock when established, and relevant deflators, we are able to recover the real investment and real capital stock in the first period as well.

TFP Estimation

With the key variables constructed, we follow the literature and use the Olley and Pakes (1996) approach to estimate the labor and capital coefficients for TFP calculation, which addresses both simultaneity and selection problems at the same time. For implementation, we use the Stata package provided by Yasar et al. (2008); please refer to their manual for the details of the estimation. The estimation is conducted separately for each industry. Year Fixed Effects are included as control variables, to take into account the dynamics of production choices in each industry. We also add "whether a firm is in the near upstream (< 5km) of a state-controlled monitoring station" as a state variable, to take into account that tighter regulations in the upstream might lead firms to make extra capital investments, even in the absence of any shocks to the underlying productivity.[33]

The estimated Log(TFP) has a mean of 3.06, and a standard deviation of 1.89. The industry-specific capital and labor coefficients are reported in Appendix Table S1 and are in general comparable to that documented in the existing literature.

[33] "Upstream proximity to a monitor" is added as a "state variable" only in the estimation of the *industry-level Olley-Pakes coefficients (β_L, β_K)*, but not in the subsequent calculation of firm-level TFP. Therefore, this state variable only helps ensure that our industry-level capital and labor coefficients are unbiased, but it does not project firm-level TFP on "upstream to a monitor" in the TFP calculation process.

The Olley-Pakes approach assumes a (conditional) monotonic relationship between investment and productivity, which might be violated if firm investments tend to be "lumpy." To address this issue, we try several different adjustments to construct alternative TFP measures for robustness checks, which will be discussed in Subsection D of Appendix E.

To understand the dispersion of our TFP measure, we follow Hsieh and Klenow (2009) and construct a variable called "TFP Ratio," which is defined as the ratio between "Firm's Log TFP" and "Industrial Average of Log TFP." The distribution of this variable is plotted in the Appendix Figure S1. As we can see, while the Log(TFP) constructed using our OP approach follows a reasonably good normal distribution, there does exist a right tail of firms that are significantly more productive than their peers in the same industry. Such large dispersion of TFP even within the same industry is consistent with the main patterns documented in the productivity literature (Syverson, 2011).

Appendix D. Qualitative Evidence on Water Quality Monitoring

A. Role of Central and Local Governments in Water Quality Monitoring

China's environmental protection strategy, while consisting of various forms of policies and programs, essentially follows one basic principle, known as "One Control and Two Standards" (*Yi Kong Shuang Da Biao*). "One Control" means controlling the total amount of annual emissions, and "Two Standards" means meeting the designated standards for emission concentration and environmental quality readings. Guided by this principle, in addition to setting national targets for total emission reduction and occasionally auditing firms' emission concentrations, a major component of the Chinese government's environmental regulation is to ensure that the readings of air/water monitoring stations meet the designated standards.

In this appendix, we summarize and review numerous policy documents from both the central and local governments in China, with a focus on how "water quality readings" are given high political priority in the environmental protection campaign. Relevant paragraphs of these policy documents are translated in Appendix F.

(1) The Role of the Central Government

The central government's policy objectives can be found in the 10th Five-Year Plan (2001–2005) and 11th Five-Year Plan (2006–2010). According to the 10th Five-Year Plan, the central government (State Council) set the policy objective that "at least 60% of the water monitoring stations should have water quality readings up to the standard according to the functional zoning of that river section".[34] In the 11th Five-Year Plan, the central government further required that "the proportion of river sections with water monitoring reading better than Grade V (on a scale of I to VI where I means the highest quality) must be no less than 78%, and the proportion of river sections with water quality better than Grade III must be no less than 57%."[35]

Following the national water quality targets announced by the State Council, the MEP issued more detailed policy guidelines, setting specific water quality requirements for all the major rivers in the country. For example, in the 10th Five-Year Plan for Huai River Protection, the MEP set specific water quality targets for all the monitoring stations in the Huai River Basin and made these requirements explicit to all the local governments. In particular, it was required that "the water quality readings of 50 monitoring stations along the mainstream of the Huai River, the water conveyance line of the "South-to-North Water Diversion" project, and the drinking water sources, should all reach Grade III

[34] http://www.gov.cn/gongbao/content/2002/content_61775.htm
[35] http://www.gov.cn/zwgk/2007-11/26/content_815498.htm

by 2005; among the remaining 49 river sections, 46 of them must have water quality readings better than Grade IV, and the remaining three no worse than Grade V".[36]

When the central government expects that local governments might fail to meet the national water quality improvement target, it issues warnings to local governments and enforces contingency regulations. Continuing with the Huai River Basin as an example, in late 2005 the MEP noticed that many monitoring stations might fail to meet the required standards (due to droughts earlier that year). The MEP issued a pollution emergency alert, demanding that local governments take immediate action.

(2) The Role of Local Governments

In response to the water quality standards set by the central government, provincial governments design their own enforcement plans and allocate the regulatory burdens to different prefectural cities and counties in their jurisdictions. Lower levels of governments then identify all the main polluting sources and calculate how much emission each polluting source should abate in order to improve the water quality readings to the required levels.

Here we use the Jiangsu province as an example to illustrate how the provincial and prefectural city governments respond to the central government's orders. Jiangsu is a rich coastal province located downstream of the Huai River Basin and the Yangtze River Basin, and has a large number of manufacturing firms. Following the SOD slogan, in 2003, Jiangsu provincial government issued a detailed Enforcement Plan (Jiangsu Environmental Protection Enforcement Plan, 2003) to the prefectural and county-level governments and required them to tighten up water quality regulations. The timeline is consistent with our empirical findings in Figure 5 that significant improvements in water quality readings happened only after 2003.

There are two important features in the Enforcement Plan. First, for each state-controlled monitoring station, the provincial government imposed a specific water quality target that had to be achieved by the end of 2005 (i.e., a water quality grade on the scale of I to VI). Second, the provincial government set the maximum allowable COD concentrations for certain monitoring stations, incentivizing local officials to target COD emissions around them.[37]

In terms of enforcement, the provincial government said that local governments should focus on industrial firms and highlighted several industries that contribute the most to COD emissions.[38] The provincial government explicitly stated in the Enforcement Plan that local governments could limit or

[36] http://www.caep.org.cn/yclm/xzzq/gh_22086/200602/W020180921440908073565.pdf

[37] Enforcement plans for total emission control and emission concentration control are also included in these policy documents, but for the purpose of this paper, we focus our discussion on the enforcement plans for water quality readings.

[38] These industries include paper pulping, brewing, chemical, starch, tanning, pharmaceutical, and printing and dyeing.

suspend the production of polluting firms when necessary. In addition, the provincial government also required polluting firms to upgrade their production and abatement technologies. The Enforcement Plan required that more than 27 large-scale water-cleaning projects must be completed by 2005, and all these projects focused on retiring/upgrading pollution-intensive technologies in the polluting plants. The total cost was estimated at around 500 million yuan (60.3 million USD). Among them, 18 projects were specifically designed to abate COD emissions, which would cost the firms more than 315 million yuan (38 million USD).

The provincial enforcement plan was then passed to prefecture and county leaders, with a customized document explaining the most important contents relevant to each prefecture/county. For example, when Huai'an prefecture city received the Enforcement Plan, four state-controlled monitoring stations in its jurisdiction were highlighted, for which the water quality readings should all reach Grade III by 2005 (Huai'an Environmental Protection Enforcement Plan, 2003). The Huai'an government then urged the local counties to regulate polluting firms in their jurisdiction and to try to upgrade the industrial structures and reduce industrial emissions.

As illustrated in the Jiangsu example, the Chinese central government indeed imposed strong political incentives on local government officials to improve the water quality readings of the national monitoring stations. Moreover, it is evident that in order to achieve the centrally designated water quality targets, local government officials are willing and able to interfere with firm production in substantial ways: temporary output restriction and production suspension of polluting firms, compulsory adoption of cleaner technologies and abatement facilities, increases in emission fees and various fines, etc.

The practices in Jiangsu province are not isolated cases. Below, we reviewed a large number of policy documents from other local governments during our study period (2000–2007), and the vast majority emphasized the importance of meeting the central government's water quality standards and outlined specific interventions on how to reduce emissions. Looking beyond our study period, we also find more recent policy documents suggesting that interference with firm production to improve water quality readings remains prevalent today.

B. Translation of Policy Documents Relevant to Water Quality Regulation

In this section, we translated a set of government policies on improving surface water quality in China during our study period. The purpose of this exercise is to provide additional qualitative evidence that supports the empirical findings in the paper. While we reviewed a large number of policy documents, here we highlight a handful of cases that we believe are representative of the entire nation's practices. To narrow down the focus, we extracted chapters/sections that are most relevant to surface water quality and monitoring stations. There are ten cases in total. Section A summarizes the policies issued by the Jiangsu provincial government to improve the Huai River Basin's water quality in 2003, 2004, and 2005. Section B gives four examples at the prefectural level: Guangzhou, Huai'an, Harbin, and Xuchang. Section C provides a county-level example (Shunde) and a river-level example (in Guizhou). Finally, in Section D, we provide a more recent mandate (2017) showing that the regulatory practices persist.

(1) Jiangsu Province's Water Quality Regulations in the Huai River Basin

Title: Notice on Printing and Distributing the "Tenth Five-Year Plan" for Water Pollution Control in the Huai River Basin, Jiangsu Province; Date: July 1st, 2003

Issuing agency: General office of Jiangsu provincial government

Notified agencies: People's governments of all cities and counties, and relevant commissions, offices and bureaus of the province, all institutions directly affiliated to the province

Copy to: Provincial Party Committee ministries, Provincial People's Congress Standing Committee Office, Provincial People's Political Consultative Conference Office, Provincial Court, Provincial Procuratorate, Provincial Military Region

Controlling Indicators:

(1) Indicators of water environment quality: permanganate index and ammonia nitrogen;

(2) Controlling total pollution discharged: chemical oxygen demand and ammonia nitrogen.

Designated Area

According to the *National Tenth Five-Year Plan for Water Pollution Control in the Huai River Basin*, the basin is divided into 7 planning areas and 111 control units which correspond to 111 control sections where water quality is monitored. Three planning areas are within or partly within Jiangsu Province, namely, Hongze Lake Planned Area covering Xuzhou (partly); Yishu River Planned Area covering Xuzhou (partly); and the Huai River Downstream Planned Area covering Xuzhou (partly), Huai'an, Suqian, Yangzhou (partly), Taizhou (partly), Nantong (partly), Yancheng, and Lianyungang. There are a total of 45 control units and 45 corresponding water quality control sections located within or partly within the jurisdiction of Jiangsu Province (See Appendix Table 1 for detailed information on planning areas, control units, and sections).

Priorities of the Plan

Strive to improve surface water quality in the region while carrying out the construction of the east-line of the South-North Water Diversion Project. According to the design plan of the east-line major project, in 5 cities, namely Yangzhou, Suqian, Huai'an, Xuzhou, and Taizhou, and 12 counties (cities) within them, water quality in control sections that have direct impact on the South-North Water Diversion Project should meet the Grade III standard by 2005 so as to meet the requirement for the water transfer.

Targets of Water Quality Control

Overall target: by the end of 2005, with the assumption that the ecological flow of the mainstream and tributaries of the Huai River is guaranteed, water quality of the mainstream of the Huai River should be further improved and the quality of water transferred via the east-line of the South-North Water Diversion Project shall basically meet the Grade III standard of surface water.

Target Breakdown

For the 31 control sections (monitoring stations) on the mainstream of the Huai River, the transfer lines of the South-North Water Diversion Project, and urban drinking water sources, the quality of water should meet the national Grade III standard. Water quality in 10 control sections should meet the national Grade IV standard and water quality in 3 other sections should meet the Grade V standard. CODcr concentration in the Huang Bridge Section of Kui River should be below 70 mg/liter (see table below for the specific water quality target for each section).

Name of Planning Area	Name of control unit	Name of control section (monitoring station)	Target water quality	Current water quality
Hongze Lake Planning Area	Kui River	Huang Bridge	*	>V
Hongze Lake Planning Area	Laobian River (Sui River)	Linhuai, Hongze Lake	III	II
Yishu River Planning Area	Yin South Little River	Zhang Zhuang	IV	IV
Hongze Lake Planning Area	Shu River	Shaoding Bridge	IV	V
Downstream Planning Area	An River	Xiaowang Zhuang	III	III
Downstream Planning Area	Chuanchang River	Dongtailianyi Bridge-Funing Brewery	III	III
Downstream Planning Area	Sheyang River	Funing phosphate fertilizer plant-Sheyang gate	III	III
Downstream Planning Area	Total irrigation canal	Suzui-Liuduozha	III	III
Downstream Planning Area	Doulonggang	Datuan Bridge-Doulongzha	III	III
Downstream Planning Area	Guang River	Xiangshui Western City Bay-Chen Gang	III	III
Downstream Planning Area	Xinyanggang	Dazong Lake exit-Xinyang gate	III	III
Downstream Planning Area	Guannan section of Yan River	Nan gate	III	III
Downstream Planning Area	Guanyun section of Yan River	Yinshan North Bridge	IV	IV
Downstream Planning Area	Main section of Rose River	Linhong gate	III	V
Downstream Planning Area	Urban section of Xiyandabu River	Xiangyang Bridge	V	>V

Downstream Planning Area	Main section of Pandan River	Dabantiao gate	V	>V
Downstream Planning Area	Main section of Qingkou River	Batou Bridge	IV	>V
Downstream Planning Area	Main section of Shian River	Puxi Bridge	IV	IV
Downstream Planning Area	Main section of Dongmengwutu River	Yanji Bridge	III	III
Downstream Planning Area	Xintongyang-Tongyu River	Guben Bridge	IV	>V
Downstream Planning Area	Sui River	Hongnong Bridge	IV	>V
Downstream Planning Area	Liutang River	Shidu	IV	>V
Downstream Planning Area	Gushan River	Xuhuai Rode	V	V
Downstream Planning Area	Huaihongxin River	Shuangou Bridge	III	III
Downstream Planning Area	Jiuligou-Hangjiapu Bridge Jiangyan section	Hangjiapu Bridge	III	III
Downstream Planning Area	Taixi-Honglin Bridge Jiangyan section	Honglin Bridge	III	IV
Downstream Planning Area	Taixi-Honglin Bridge Taizhou section	Taidong	III	V
Downstream Planning Area	Zhuzhuang-Xinghua Taizhou section	Zhuzhuang	III	III
Downstream Planning Area	Zhuzhuang-Xinghua Xinghua section	Refrigeration plant	III	III
Downstream Planning Area	Yangzhou section of Dayun River	ShiQiao lock	III	>V
Downstream Planning Area	Guyun River	Xinkai River	III	>V
Downstream Planning Area	Baoshe River	Wangzhi power plant	IV	>V
Downstream Planning Area	Yanzhou section of Tongyang River	Youku Bridge	IV	>V
Downstream Planning Area	New Tongyang River	Jiangdu West lock	III	IV
Downstream Planning Area	Beichengzi River	Gaoyou	III	>V
Downstream Planning Area	Water channel flowing into Changjiang River	Jin Lake	III	IV
Downstream Planning Area	Xuyi section of Huai River	Laozi Mountain	III	V
Downstream Planning Area	Huaiyin section of Dayun River	Huaiyin	III	>V
Downstream Planning Area	Suqian section of Dayun River	Suqian	III	IV
Downstream Planning Area	Pizhou section of Dayun River	Pizhou	III	>V
Downstream Planning Area	Bulao River	Linjiaba	III	>V
Downstream Planning Area	Fangting River	Tu Mountain	III	>V
Downstream Planning Area	Peiyan River	Pei River	III	>V
Downstream Planning Area	Xusha River	Shaji West lock	III	V
Downstream Planning Area	Fuxing River	Fuxing lock	III	V

Promoting the Review of Clean Production in Key Areas and Industries

The review of provincial-level key polluting sources should be completed by 2004, and in 2005 all key polluting sources need to be reviewed for clean production compliance. ISO 14000 environmental management system certification needs to be carried out in enterprises where the situation allows.

A discharging permit system and a cap on the total amount of pollutants discharged should be put in place to reduce major pollutants (CODCr and NH3-N) and other criteria pollutants. Pollution treatment facilities should be managed in a standardized fashion, run by non-government entities and capable of automatic monitoring. Consolidate the achievement of meeting the pollution sources discharge standard.

Law Enforcement

Law enforcement needs to be strengthened so that violations against the law will be investigated and dealt with thoroughly. The 15 types of small enterprises (which are deemed to be heavy polluters by the State Council) and the 5 new types of enterprises (which are classified as environment-polluting, over-exploiting, low-quality product producers with outdated equipment and unsafe production lines by the National Commission on Trade and Economy, now the Ministry of Commerce, and the National Development and Reform Commission), should be totally shut down for good.

Industrial pollution sources that constantly fail to meet standards should undergo structural reforms, such as closing down, production suspension, merging, and product switching, in particular companies in industries such as papermaking, brewing, chemical, starch, leather, pharmaceutical, dye intermediate, and printing and dyeing. For enterprises discharging pollutants but failing to meet the standard, a timeline should be set up for corrective measures to be taken.

Clean Investment and Financing

There are a total of 18 projects on the comprehensive treatment of industrial point-source pollution in the Huai River Basin in Jiangsu Province, with an investment totaling 315 million yuan. Among them, 9 projects, with investment totaling 180 million yuan, have been included in the industrial pollution treatment projects listed in the *Plan on Pollution Treatment of the East Line of the South-North Water Diversion Project.* (See table below for specific information on the projects.) The total investment is estimated to be around 305 million yuan, most of which will be raised by the enterprises themselves. The provincial government provides some subsidized loans on the technological renovation. Projects that are included in the east-line South-to-North Water Diversion project are eligible to apply for national subsidized loans according to relevant policies.

Name of the project	**Investment (10,000 yuan)**	**Yearly COD reduction (ton)**	**Deadline for Completion**	**Notes**
Yangzhou Kyoto Qiu Leather co. LTD	3000	160	2005	*
Hanjiang Ocean Chemical Industry co. LTD	1500	24	2005	*
Jiangdu East Asia Fine Chemical Plant	1000	160	2005	*
Gaoyou Paper-Making	7000	5400	2005	*
Gaoyou Cloth Factory	1000	120	2005	*

Improve Project of Jiangdu Synthesis Chemical Plant	1200		2005	
Upgrade Project of Jiangdu Silk Factory	900	1188	2005	
Upgrade Project of Subei Chemical Plant	1000	213	2005	
Upgrade Project of Petrochemical plant	1200		2005	
Lianyungang Alkali Plant	1000	167	2005	
Lianyungang Star Plastic co. LTD	1000		2005	
Zhengda Tianqing Pharmaceutical co. LTD	1250		2005	
Yancheng Lianfu Petrochemical co. LTD	900		2005	Finished
Yancheng Electrochemical Factory	2000		2005	
Binhai Double Lamp Group	5000	1000	2005	
Dongtai Molybdenum Acid Factory	700		2005	
Dongtai Jiuxing Paper Co. LTD	1000	600	2005	
Dafeng Zhefeng Group	500	42	2005	Finished
Total	31500			

Title: Notice of Provincial Department of Environmental Protection on "Opinions on Water Pollution Prevention and Control of the Tai Lake and Huai River in 2004"

Date: April 15th, 2004

Issuing agency: General office of Jiangsu provincial government

Notified agency: People's governments of all cities and counties, and relevant commissions, offices, and bureaus of the province, all institutions directly affiliated with Jiangsu province

Copy to: Jiangsu Provincial Party Committee ministries, Jiangsu Provincial People's Congress Standing Committee Office, Jiangsu Provincial People's Political Consultative Conference Office, Jiangsu Provincial Court, Jiangsu Provincial Procuratorate, Jiangsu Provincial Military Region

2004 is a key year for implementing the 10th Five-Year Plan for the prevention and control of water pollution in Lake Taihu and the Huai River. The following plans are put forward to control water pollution in Lake Taihu and the Huai River in 2004.

Identify Key Tasks and Implement Comprehensive Measures to Control Water Pollution in Lake Taihu and Huai River

All localities should continue to work on the overall objectives of water pollution control in Lake Taihu and the Huai River with an emphasis on the Meiliang Lake region of Lake Taihu, the main rivers that flow into and out of Lake Taihu, the upstream region of the provincial sections, and the regions along the South-to-North Water Diversion Project, and should vigorously implement various measures to prevent and control water pollution in Lake Taihu and the Huai River. Work should be sped up to ensure that the water transfer pump station of Meiling Lake will be constructed on time, the Yangtze River-Meiliang Lake-Wuli Lake water transfer plan can be implemented, and the dredging work at Meiliang Lake will be carried out.

The focus should be on the heavily polluted rivers that flow into and out of the lake, and comprehensive water treatment should be carried out in small watersheds. Tighter supervision needs to be imposed on polluting enterprises in the upstream region of the inter-province sections, the west bank of Lake Taihu, and the regions along the South-to-North Water Diversion Project, in order to strictly prevent any firm from reverting to the old pollution path. Structural adjustment of heavily polluting industries, such as papermaking, cement, printing, dyeing, and chemical industries, should be facilitated. Lime pulping, yellow strawboard manufacturers with annual output of less than 20,000 tons, and other chemical pulp production companies with annual output less than 50,000 tons must be eliminated completely.

An extensive clean production audit has to be carried out in major polluting enterprises, and pollutant discharge standards should be increased for printing and dyeing enterprises. Quicker steps need to be taken to adjust sewage treatment fees, build municipal wastewater treatment plants, and start the construction of already-committed projects in the first half of this year. Together with the structural adjustment of the agriculture sector, efforts should be made to actively develop ecological agriculture and organic agriculture and to reduce agricultural non-point-source pollution.

The National 863 Program-Lake Taihu Initiative needs to be further enhanced to make water pollution control more science-driven. Regulations on the prevention and control of ship pollution in the inland waters of Jiangsu province also have to be implemented in a conscientious way so as to form a legal basis for the prevention and control of ship pollution. Ecological protection barriers should be built and ecological protection projects should be carried out along the lakeshore of Lake Taihu, in the water source of the east route of the South-to-North Water Diversion Project, and along the water transfer lines.

Strengthen Leadership

The government should strengthen organizational leadership and establish a work responsibility system for controlling water pollution in Lake Taihu and the Huai River. Controlling water pollution in Lake Taihu and the Huai River relies on the attention received from and efforts made by different levels of government. Relevant government agencies at all localities should put water pollution control on their agenda and include it in the local economic and social development plan. The chief government official should lead, relevant officials should take specific responsibilities, and relevant departments should implement specific tasks. The administrative chief is responsible for achieving the environmental protection targets and must consider water pollution control for Lake Taihu and the Huai River as a first-order task. The pollution treatment work should be clarified and delegated to local government organizations, to specific projects, and to responsible units and staff.

The mechanism for assessing the leading official’s performance shall be conscientiously implemented. It will consider target realization status, especially water pollution control achievement, as a key criterion. Relevant provincial government organizations should perform their duties, strengthen coordination, supervision, and inspection, and push forward the implementation of various tasks in the control of water pollution. Environmental protection departments at all levels should give feedback and advice to the government, regularly report the situation, put forward work proposals, strengthen environmental management of construction projects, and strengthen environmental protection law enforcement.

Decomposition Table of Water Pollution Prevention Target Task in Tai Lake 2004

Category	Aims and tasks	Requirements	Responsible units
Industrial pollution	Implement clean production audit	To complete the clean production audit of 180 units in 2003, and complete the clean production audit of 250 enterprises in this year, including 120 in Wuxi, 30 in Changzhou, 90 in Suzhou, and 10 in Zhenjiang.	Relevant governments in cities and counties, provincial economic and trade commission, environmental protection department.
	Improve industrial wastewater discharge compliance rate	Strengthen the supervision of industrial pollution sources, and continue to help 7 industrial pollution sources with their phosphorus removal and nitrogen removal projects, including 6 in Changzhou and 1 in Suzhou, to ensure that the industrial wastewater discharge compliance rate reaches 90% or above.	
	The pollutant emissions in printing and dyeing industry should be subject to the first-level emission standard	All printing and dyeing enterprises in the Tai Lake Basin must strictly control pollution. By 2005, the pollutant discharge should reach the first-level emission standard. In 2004, all printing and dyeing enterprises must formulate plans and start implementation.	
	Promote the adjustment of industry structure, and Strictly control new sources of pollution	The first-level and second-level protected areas in Tai Lake should strictly implement the relevant provisions of the "Regulations on the Prevention and Control of Water Pollution in Tai Lake of Jiangsu Province". Structural adjustments in the printing and dyeing and chemical industries should be carried out, in order to consolidate and improve the achievements of industrial structure and product adjustment in Shengze Town.	

Control Plan for Total Phosphorus Pollution Source in Tai Lake Basin 2004

No.	Names	Total Phosphorus reduction (ton/year)	Investment estimation (10,000 yuan)	Progress status in 2003	Requirements in 2004
1	Changzhou Agricultural Pharmaceutical Factory	0.6	55	Under construction	Complete the treatment
2	Changzhou Black Peony Yarn-Dyed Knitting co. LTD	0.5	44	Under construction	Complete the treatment
3	Changzhou Pharmaceutical Factory	0.5	41	Under construction	Complete the treatment

Control Plan for Ammonia Nitrogen Pollution Source in Tai Lake Basin 2004

No.	Names	Ammonia Nitrogen Reduction (ton/year	Investment estimation (10,000 yuan)	Progress status in 2003	Requirements in 2004
1	Jiangsu Chrysanthemum MSG Group	103.7	1397	Under construction	Continue the treatment and complete it in the first half of 2005
2	Liyang Silk Spinning Factory	5.6	76	Under construction	Complete the treatment
3	Changzhou Dongfang Pretreatment & Finishing Factory	1.1	15	Under construction	Complete the treatment
4	Changzhou Flocking Material Factory	17.3	233	Under construction	Complete the treatment

Huai River Water Pollution Prevention Task and Water Quality Protection Task Breakdown Table for South-to-North Water Transfer East Line 2004

Category	Contents	Requirements	Responsible Units
Industrial Pollution Control	Industrial structure adjustment	Adjust the structure of heavily polluting industries such as papermaking and chemical industry, formulate and implement the elimination of the lime paddle making process, and eliminate other chemical paddle production enterprises with annual output less than 20,000 tons of yellow cardboard and total annual output less than 50,000 tons. Prevent the resurgence of the "Fifteen Small" enterprises in the process of industrial gradient transfer.	Governments of relevant cities and counties, provincial economic and trade commission, and environmental protection department
	Carry out clean production audit	Complete 50% of the clean production audit of key pollution sources	
	Improve industrial wastewater discharge compliance rate	Strengthen the supervision over industrial pollution sources and ensure that the industrial wastewater discharge compliance rate remains above 90%	Governments of relevant cities and counties, and the environmental protection department

Title: Notice on Water Pollution Control in the Huai River Basin

Date: March 21st, 2005

Issuing agency: General office of Jiangsu provincial government

Notified agencies: People's governments of all cities and counties in Jiangsu, and relevant commissions, offices, and bureaus of the province, all institutions directly affiliated with Jiangsu Province

Copy to: Jiangsu Provincial Party Committee ministries, Jiangsu Provincial People's Congress Standing Committee Office, Jiangsu Provincial People's Political Consultative Conference Office, Jiangsu Provincial Court, Jiangsu Provincial Procuratorate, Jiangsu Provincial Military Region

The water pollution control policies for the Huai River are guided by the important thoughts the *Scientific Outlook on Development*. The policies are designed to meet the requirements of building a harmonious socialist society, improving the prosperity of the people, and strengthening the province, as well as accomplishing the '*Two Priorities*' (namely taking the lead in building a moderately prosperous society in all respects and in basically realizing modernization)…. The economic development model should be effectively changed and a circular economy should be actively promoted. Reforms should be carried out to improve efficiency and understand the mechanisms behind environmental protection. Systematic and scientific methods should be adopted to treat the water environment. The role of the market should be utilized, and various economic and legal methods should be used to realize the pollution treatment target at each phase, improve the water quality of the Huai River, and promote sustainable economic and social development.

By the end of 2005 and with a normal water inflow, the water quality of the mainstream of the Huai River and its 33 major tributaries should be improved. The water quality of 4 provincial sections should basically meet the requirements of *The 15th Five-Year Plan of Water Pollution Prevention and Control in the Huai River Basin* (hereafter referred to as '*The Plan*'). The COD and ammonia nitrogen emissions should be reduced by 20% and 10% respectively relative to their 2000 levels. Over 60% of the pollution prevention and control engineering projects listed in *The Plan* should be put into operation.

By the end of 2007 and with a normal water inflow, the water quality of the mainstream of the Huai River, its 33 major tributaries, and its 4 inter-province sections should be further improved. The water quality of rivers along the South-to-North Water Diversion Project region should reach Grade III. Over 60% of the sections of the main tributaries should enjoy Grade V-and-above water quality. The COD and ammonia nitrogen emissions should be reduced by 25% and 15% respectively relative to their 2000 levels. Over 90% of the pollution prevention and control engineering projects listed in *The Plan* should be put into operation. The sewage wastewater treatment rate in prefectural cities should not be lower than 70%, and that of the county-level cities and counties should not be lower than 40%.

By the end of 2010 and with a normal water inflow, the water quality of the mainstream of the Huai River and its 33 tributaries should meet the water functional environmental zone requirements. The sewage wastewater treatment rate in prefectural cities should not be lower than 80%, and that of the county-level cities and counties should not be lower than 55%.

Strengthen Regulations on Polluting Industrial Enterprises

Following the national regulations, outdated production capacity, technology, and products should be retired according to the schedule. To upgrade the economic structure and better control pollution, enhanced regulations should be imposed on the heavily polluting industries, such as papermaking, brewing, pharmaceutical, tanning, printing and dyeing, and chemical industries. By the end of 2005, the following production lines need be closed: all lime pulping, chemical pulp production with an annual pulping capacity of less than 34,000 tons, yellow strawboard companies with an annual capacity of less than 10,000 tons, wastepaper papermaking enterprises with an annual production capacity of less than 10,000 tons, and alcohol and starch production lines with an annual capacity of less than 10,000 tons. Enhanced supervision and management of industrial pollution sources should be put in place. Enterprises that cannot meet the water pollutant standards in a stable way should be suspended from production. Enterprises that discharge beyond the standard or those meeting the standards but still having a high discharge volume shall be included in the Provincial Environmental Protection Commission's list of mandatory clean production enterprises. The list should be published to the public and additional supervision should be imposed on these enterprises. Clean production audits should be done on 56 enterprises which are listed as target polluters. Starting in 2007, enterprises that still cannot meet the total emission control requirements should be restricted from production and emission.

(2) Prefectural-Level Regulations

Title: Notice on Printing and Distributing the "Implementation Plan of the Guangzhou Pearl River Comprehensive Remediation 2003-2010" and the "Guangzhou Pearl River Comprehensive Remediation Work Plan 2003"

Date: March 30th, 2003

Issuing agency: People's government of Guangzhou City

Notified agencies: People's governments of all districts and counties, and relevant units belonging to Guangzhou City

Regulation Objectives

In accordance with the requirements of the *Decision of the CPC Party Committee and the People's Government of Guangdong Province on Strengthening the Comprehensive Treatment of the Pearl River* and the *Responsibility Letter for the Treatment of the Pearl River,* the target of the comprehensive treatment of the Pearl River in our city is the following: by the end of 2003, the amount of black and odorous water flowing through urban rivers should be significantly reduced, and the water quality should reach Grade V based on the *Surface Water Environmental Quality Standard* (GB3838-2002). By 2005, the water quality of the main drinking water sources should meet the functional requirements; the water quality compliance rate at the provincial (including national) monitoring sections should reach 75%, and the water quality compliance rate at the cross-city (district) river junction sections should also reach 75%. The black and odorous water flowing through urban river reaches should be largely eliminated. The rate of industrial wastewater discharge complying with the standard should reach 90%, and the urban sewage wastewater treatment rate should reach 60%. By 2010, all the main surface waters and coastal waters should meet the functional requirements. The water quality compliance rate at the provincial (including national) monitoring sections should reach 80%, and the water quality compliance rate at the cross-city (district) river junction sections should also reach 80%. The rate of industrial wastewater discharge complying with the standard should reach 95% or more, and the urban domestic sewage wastewater treatment rate should reach 70%. The Guangzhou segment of the Pearl River should become clear, the water quality in the western channel should be better than Grade III, the water quality of the front and rear channel and Huangpu channel should be better than Grade IV, and the organic pollution flowing through the Guangzhou segment of the Pearl River and other urban river reaches should all be significantly improved.

The Gap between Current State and the Target

In recent years, the Municipal Party Committee and the Municipal Government have attached great importance to the cleaning up and protection of the Pearl River. Investment in environmental protection has increased year by year—17.578 billion yuan was invested during the 9th Five-Year Plan period, accounting for 1.83% of the city's GDP, and 5.717 billion yuan in 2001, which amounted to 2.13% of the total GDP. With efforts made to achieve the "One Control Two Standards" target, i.e., controlling the total amount of pollutants discharged and meeting the standards set for industrial pollutants and for ambient water quality, the total emissions of major pollutants have been significantly reduced relative to the 1996 levels. The city's 2,941 industrial pollution sources that were under assessment have all met the national standards and requirements. Meanwhile, the construction of infrastructure needed for environmental protection is speeding up, and the rate of domestic sewage treatment is increased through the city's campaign of "making notable differences in three years' time," which focused on improving urban infrastructure and the environment.

Up to now, three sewage wastewater treatment plants have been built in the city, namely the Datansha Sewage Treatment Plant, the Liede Sewage Treatment Plant (Phase I), and the Development Zone Sewage Treatment Plant, with daily sewage wastewater treatment capacities of 330,000 tons, 220,000 tons, and 30,000 tons respectively and combined capacity of 580,000 tons. In 2002, the centralized treatment percentage of urban domestic sewage was 29.28%. The plants in Liede and Datansha are currently being expanded and constructed in Phase II and Phase III respectively. Three more treatment plants are being built (Xilang Sewage Treatment Plant Phase I, Lijiao Sewage Treatment Plant Phase I, and Panyu Qianfeng Sewage Treatment Plant Phase I). At the same time, progress has been made in pipe network construction and sewage interception projects. Construction of intercepting boxes, covering areas from Xihaochong and Donghaochong to the Liede Sewage Treatment Plant in the Pearl River new city, as well as in Yanjiang Road, has been completed. These boxes have intercepted most of the effluent in the northern bank of the upper Pearl River waterway, which helped improve the water quality.

When comparing against the national Environmental Quality Standards for Surface Water (GB3838-2002) promulgated and implemented in 2002, 19 out of 24 water quality indicators, such as biochemical oxygen demand of the Pearl River in Guangzhou, met Grade III standards in 2001. Only 5 indicators, namely ammonia nitrogen, total nitrogen, total phosphorus, dissolved oxygen, and fecal coliform did not meet the Grade III standard. Among them, total nitrogen and ammonia nitrogen were worse than Grade V standards. The annual water quality was better than in 2000 and 1996. The large areas of black and odorous waters that used to appear during dry seasons in the mid-1990s can no longer be found today.

The government should focus on industrial pollution from electroplating, textile printing and dyeing, leather-making, chemical, building materials, smelting, papermaking, and fermentation enterprises, and continue to enforce strict standards for the discharge of industrial wastewater. By December 30th, 2005, 15 industrial enterprises with more than 65% of the water pollution load of our city should fully comply with the standards for the discharge of industrial wastewater, including Guangzhou Papermaking Co., Ltd., Sinopec Guangzhou Branch, Guangzhou Iron and Steel Co., Ltd., Guangdong Yuehua Power Generation Co., Ltd., Guangzhou Pearl River Beer Group Company, Guangzhou Hengfeng Dyeing and Finishing Co., Ltd., Guangdong Nanfang Soda Ash Manufacture Co., Ltd., Guangzhou Oil & Gas Plant, Guangzhou Victorgo Industrial Co., Ltd., Guangzhou Shipyard International Co., Ltd., Guangzhou Tianxin Pharmaceutical Co., Ltd., Guangzhou Yongda Group

Company, Guangzhou United Meat Processing Plant, Panyu Dongyong Liye Bleaching and Dyeing Co., Ltd., and Plant A of Guangzhou Victorgo Industrial Co., Ltd. We will strengthen the wastewater treatment efforts for industrial enterprises located in the water source protection zone, along the banks of the Pearl River and Liuxi River, as well as those that are currently unable to reliably meet the standards, so as to comprehensively improve the industrial wastewater treatment rate and the standard compliance rate. We will also build Xintang Xizhou Environmental Protection Industrial Park in Zengcheng, introduce and guide the plants that have moved out of the secondary water source protection zone into the industrial park to implement clean production and centralized pollution control.

Prevention and Treatment of Industrial Pollution

The government should make great efforts in the treatment of industrial pollution sources, and start the work on fully meeting the standards for the discharge of wastewater from industrial enterprises, with emphasis on 15 industrial enterprises including Guangzhou Papermaking Co., Ltd., Sinopec Guangzhou Branch, Guangzhou Iron and Steel Co., Ltd., Guangdong Yuehua Power Generation Co., Ltd., Guangzhou Pearl River Beer Group Company, Guangzhou Hengfeng Dyeing and Finishing Co., Ltd., Guangdong Nanfang Soda Ash Manufacture Co., Ltd., Guangzhou Oil & Gas Plant, Guangzhou Victorgo Industrial Co., Ltd., Guangzhou Shipyard International Co., Ltd., Guangzhou Tianxin Pharmaceutical Co., Ltd., Guangzhou Yongda Group Company, Guangzhou United Meat Processing Plant, Panyu Dongyong Liye Bleaching and Dyeing Co., Ltd., and Plant A of Guangzhou Victorgo Industrial Co., Ltd.

The government should strengthen the supervision and law enforcement of pollution sources, increase penalties for those that leave pollution treatment facilities idle or discharge pollutants without permission, and ensure that pollutants are discharged in accordance with standards in a sustained and stable manner.

In accordance with the unified deployment and requirements of the provincial government, we will carry out the unified planning and designated work of heavy-polluting industries such as electroplating, textile, printing and dyeing, leather-making, chemical, metallurgy, and papermaking industries, and propose projects which need to be treated with a strict timeline and those which need to be closed, suspended, merged, or transferred, and follow up and implement them.

Before the end of October 2003, the large-scale livestock and poultry farms that fail to reach the standard after the deadline for sewage treatment shall suspend production for rectification or be closed.

By the end of 2003, the government should clean up and rectify the printing, dyeing, electroplating, and other heavy-polluting enterprises in the secondary protection zones for drinking water sources.

We will continue to clean up and rectify the printing, dyeing, and rinsing industries in the secondary protection zone in Xintang area, speed up the construction of Xizhou Environmental Protection Industrial Park in Xintang, and strive to relocate some printing and dyeing enterprises in the secondary protection zone for drinking water sources to the industrial park, so as to create conditions for completing the task of closing or relocating the printing and dyeing enterprises in the secondary protection zone before the end of 2005.

Title: Notice of People's Government of Harbin on Printing and Distributing the "Implementation Plan of Water Pollution Prevention and Control in Harbin Section of Songhua River Basin"

Date: April 26th, 2006

Issuing agency: People's government of Harbin City

Notified agencies: People's governments of all districts and counties, and relevant commissions, offices, and bureaus of the municipal government

With the Plan as guidance, the creation of the national model city for environmental protection as the carrier, and the protection of safe drinking water sources and the construction of urban sewage treatment plants as the key, we shall strictly control industrial pollution, speed up the improvement in the river basin environment, reduce non-point-source pollution, strengthen regulation, investment and monitoring, and ensure that the water quality of the river basin meets the water quality standards of various functional areas, so as to promote the coordinated development of the economy, society, and ecological environment.

Prevention and Control Target

Overall target: by 2010, the major water pollutants should be reduced by more than 15% compared with the 2005 levels. The water quality compliance rate of urban centralized drinking water sources should be higher than 96%, and that of agricultural irrigation, fishery, and industrial water functional zones should reach 100%. Over 90% of urban sewage should be treated and over 50% of municipal domestic sewage should be treated. The water quality of the Harbin section of the Songhua River should reach the Grade III standard, and the water quality of 14 primary tributaries should reach their corresponding standards. The water environment quality of the river basin should be greatly improved.

Short-term target: by 2006, the emissions of major water pollutants should be reduced by 2,000 tons. The water quality compliance rate of urban centralized drinking water sources should be higher than 96%, and that of agricultural irrigation, fishery, and industrial water functional zones will reach 96%. Twelve sewage treatment plants should begin construction. The 3rd phase construction of Wenchang City sewage treatment plant should be completed, and 67% of urban sewage should be treated. By

2007, emissions of the major water pollutants should be reduced by 10,000 tons. The water quality compliance rate of urban centralized drinking water sources should be higher than 96% and that of agricultural irrigation, fishery, and industrial water functional zones will reach 100%. The construction of eleven sewage treatment plants should be completed. Over 70% of urban sewage should be treated.

Comprehensive Improvement of the Water Source Protection Zone.

By the end of June 2006, the Municipal Environmental Protection Bureau should lead relevant departments to conduct a detailed investigation of the pollution status in the designated protected areas. Sewage outlets and net cage culture in the Grade I protection zones should be cleared and prohibited; agricultural arable lands should be abolished in these areas; fish feeding and other economic activities that would affect the water quality, such as artificial fertilizer and aquatic tourist activities, should be banned in these areas; enterprises and public institutions that would impose a pollution threat to drinking water sources in the Grade II protection zones must shut down, be suspended, or be revamped within a time limit; new sewage outlet construction should be prohibited, and land and vegetation development in the protected zones needs to be under strict control. The Municipal Urban Management Bureau is responsible for shutting down the Chengjiagang garbage disposal plant and taking pollution treatment and control measures.

Strengthen Water Quality Monitoring and Control

Follow-up work needs to be carried out to continue monitoring the Songhua River water pollution incident. Work has to be done every month to monitor the water quality of the city’s water source region. A complete examination of water quality should be carried out on the urban centralized drinking water sources every year and relevant information should be published in a timely manner. A water-environment information exchange mechanism should be built to better communicate with the upstream cities so as to monitor the water quality changes in a timely manner.

Treatment of Key Industrial Pollution Sources

In 2006, 100 pollutant discharging enterprises, such as Harbin Gas Factory and Harbin Pharmaceutical Group General Pharm Factory, that could not meet the pollution emission standards or could not meet these standards in a stable way were asked to treat their pollution within a certain time limit. By 2010, 500 key pollutant discharging companies such as pharmaceutical, chemical, slaughter, food, and electroplating were treated within the prescribed limit of time.

In accordance with the new standards, by 2006, 20 medical institutions shall complete their pollution treatment tasks within a certain time limit, and 200 medium-sized and above catering service companies should complete their tasks for treating wastewater sources within a certain time limit. By 2010, all medical institutions should finish their pollution treatment tasks.

Clean Production

In 2006, mandatory audits should be carried out in 80 heavy-polluting enterprises such as pharmaceuticals, chemicals, electroplating, and slaughtering enterprises to push for clean production. One hundred clean production and circular economy projects should be launched. By 2010, the numbers should reach 400 and 600, respectively.

Title: Notice on Printing and Distributing the "Tenth Five-Year Plan" for Water Pollution Control in the Huai River Basin of Huai'an City

Date: December 14th, 2003

Issuing agency: People's government of Huai'an city

Notified agencies: People's governments of all districts and counties, and relevant commissions, offices and bureaus of Huai'an city, all institutions directly affiliated with Huai'an city

Priorities of the Plan

The administration is striving for better water quality in the region while carrying out the construction of the east-line of the South-North Water Diversion Project. According to the design plan of the east-line project, the following districts and counties have a direct impact on the South-North Water Diversion Project: Qinghe District, Qingpu District, Huaiyin District, Chuzhou District, Xuyi County, Jinhu County, Hongze County, and the Economic Development Zone. They should all meet the Grade III standard by 2005 in order to fulfill the requirements for the project.

Further Breakdown of the Total Emission Control Targets

Specific plans should be developed to control the total amount of ammonia nitrogen as required by the provincial government, and they should be circulated together with the COD total amount control plan to different localities for implementation.

Improving Fundraising

Funding sources should be identified for pollution abatement projects, including market financing, government investment, and technological and economic policy adjustments, etc. This is to ensure the smooth implementation of the projects.

The Overall Target for Water Pollution Prevention and Control during the 10th Five-Year Plan

By the end of 2005, under the prerequisite that the ecological flow of the mainstream and tributaries of the Huai River is ensured, water quality of the mainstream of the Huai River should be further improved and the quality of water transferred via the east-line of the South-North Water Diversion Project should basically meet the Grade III standard of surface water.

Target breakdown: in control-monitoring sections of the mainstream of the Huai River, the transfer lines of the South-North Water Diversion Project, and drinking water sources in cities and towns, the quality of water should meet the Grade III standard.

Title: Notice on Further Strengthening the Management of Outbound Water Responsibility Targets

Date: June 18th, 2007

Issuing agency: Office of the people's government of Xuchang City

Notified agencies: People’s governments of all districts and counties, economic development zones, Dongcheng district management committee, relevant departments of the municipal people’s government in Xuchang City

Water Quality Targets at Trans-Border Monitoring Stations

In accordance with the principle of differentiated management and prioritization, monitoring stations at both city and county level are to be set up to fully reflect the quality of water in different jurisdictions. City-level control sections are set up in key areas including the Qingyi River basin, drinking water sources, and rivers that run through the urban area of counties (cities and districts). For other water bodies, county-level control-monitoring sections are set up. There are 17 city-level control sections, 3 of which serve as references, and 22 county-level control sections in the city. Targets for leave-boundary sections are determined by the environmental protection liability statement, the reduction plan on major pollutants, requirements on water quality for the "Model City" and the function zoning of the water environment. The monitoring pollutant is COD. See below for specific information on water quality targets for the leave-boundary monitoring sections.

Calculation for Standard-Exceeding Water Quality in Leave-Boundary Sections

Calculation method for exceeding multiple of the monitoring results of river leave-boundary sections: Exceeding multiple=(measured concentration-target value)/target value

When the concentration of the monitored pollutant is lower than or equal to the target value, the water quality is deemed to be within the limit and the above calculation method will not be applied.

Penalties through Fiscal Deduction

When the exceeding multiple of leave-boundary sections monitored in counties (cities and districts) is below 0.5 (including 0.5), a 70,000 RMB fee will be charged for each violation; 150,000 RMB for multiples between 1 and 1.5 (including 1.5); 250,000 RMB for multiples between 1.5 and 2 (including 2); and 300,000 RMB for multiples higher than 2. Counties (cities and districts) with more than two control sections will be charged in an accumulative way.

The monthly peak monitoring result of the out-flowing controlled section in each county (city and district) determines the amount of money to be charged. If there are 2 consecutive violations, the actual deduction will be doubled. If there are 3 consecutive violations, the actual penalty will be 1.5 times more for the additional violations. And if there are 4 consecutive times, the actual payment will be 2 times more for the additional violations.

If the monitoring result of a control section is more than double the target level, the county (city and district) government shall take measures to strictly limit the production of and the amount of pollution discharged by enterprises that exceed emission standards. If the monitoring concentration is more than 2 times higher than the target level, the municipal environmental authority should suspend the approval of construction projects that will increase the total amount of pollutant discharge in the county (city and district) concerned.

(2) County-Level and River Level Regulations

Title: Notice on the "Comprehensive Improvement Plan for the Water Environment in Shunde District, Foshan"

Date: March 3rd, 2003

Issuing agency: People's government of Shunde District, Foshan

Notified agencies: People's governments of all townships, Street Offices, and relevant units belonging to Shunde district

Industrial pollution regulation needs to be strengthened. There are a large number of industrial enterprises scattered across Shunde, including a certain number of polluting enterprises. Starting from 1999, 186, 499, and 601 polluting enterprises were required to control pollution within a time limit through the three phases of the "One Control Two Standard" campaign, and these enterprises had generally reduced emissions of major pollutants. Yet, most polluting enterprises have not fully met the discharge standard. Hazardous industrial waste has only been treated briefly, and standardized treatment has not yet been carried out. Pollution accidents in industrial enterprises still occur from time to time, resulting in frequent complaints from citizens about environmental issues.

Objectives for the Comprehensive Improvement of the Water Environment

The overall objective of comprehensive improvement of the water environment in Shunde is: initial improvement should be achieved in the first year, and rivers should be neither black nor odorous in 3 years and ultimately become clear in 8 years.

Through treatment, all river reaches should meet the requirements set forth in the *(Trial) Plan for Functional Zoning of Surface Water Environment in Guangdong Province*, which will guarantee a qualified water supply, clear water environment, and balanced ecology for urban construction and economic development. The realization of the objective is to promote the sustainable development of the economy, the society, and the environment.

By the end of 2003, the water quality of the main rivers should meet the corresponding functional requirements of the environment. The organic pollution in rivers flowing through cities and towns should be alleviated, and the amount of black and odorous water should be significantly reduced. In Daliang, Ronggui, and Lunjiao, located in central urban areas, sewage treatment plants should be built and put into operation, and initial improvement should be achieved in river branches in towns and streets.

By the end of 2005, the water quality of the main drinking water sources should meet the functional requirements; the water quality compliance rate at the provincial (including national) monitoring sections should reach 75%, and the water quality compliance rate at the cross-city (district) river junction sections should reach 75%. The water quality of some heavily polluted rivers flowing through cities and towns should be significantly improved, and black and odorous waters flowing through urban river reaches should be basically eliminated; the standard compliance rate of industrial wastewater discharge should reach 92% or more; the domestic sewage treatment capacity in operation should exceed 350,000 tons/day, and the urban domestic sewage treatment rate should reach 50%.

By the end of 2010, all the main surface water quality should meet the functional requirements. The water quality should be maintained at a good level, and all the drinking water sources should meet the functional requirements. The water quality compliance rate at the provincial (including national) monitoring sections should reach 80%, and the water quality compliance rate at the cross-city (district) river junction sections should reach 80%. The standard compliance rate of industrial wastewater discharge should reach 95% or more; the domestic sewage treatment capacity in operation should exceed 550,000 tons/day, the urban domestic sewage treatment rate should reach 70%, and the organic pollution flowing through urban river reaches will be significantly improved.

Strictly Control Pollution Sources

After the industrial sources meet the discharge standard, we should further make all the polluting sources meet the discharge standard. Among them, all the key polluting enterprises should comply fully with the discharge standard. We will continue to control the total amount of pollutants discharged, actively implement the polluting permit management system, expand the coverage of polluting permits, and exercise strict management.

Title: Water Quality in Qingshui River Deteriorated and Relevant Government Agents Responded, Guizhou Province

It is well understood that the Qingshui River, located in Guizhou Qiannan Prefecture, is the main section of the upstream of Dongting Lake. In recent years, the total phosphorus and fluoride in the water bodies of the Qingshui River and its tributary, the Chong'an River, have seriously exceeded the standards, and the water quality has deteriorated year by year. After being verified by the environmental protection departments, this was due to the pollution of Chong'an River, which was caused by the emissions from several phosphorus chemical companies in Fuquan City.

On July 1st, relevant provincial officials organized an on-site meeting for relevant departments and executives of phosphorus chemical companies along the Chong'an River in Fuquan City to address the water pollution issue. During the meeting, provincial officials commented that to treat the Chong'an River water pollution, the first step was to have all companies meet the emission standards; the second step was to control the overall discharge volume. Environmental protection departments should require companies to treat their pollution within the time limit; otherwise, the companies would be shut down. And the target was to ensure that people living along the river could enjoy clean water and clear sky.

(4) A Recent Example

An Order Issued by Kunshan Government to Improve Water Quality around the Monitoring Stations in 2017

Kunshan 263 Special Action Team Office

Kunshan 263 Office【2017】 #186

An Urgent Order on Suspending Production of Industrial Enterprises Located in the River Basin of Wusong River Zhaotun (Shipu) Water Quality Monitoring Station and Two Other River Basins

To Kunshan Development Zone, Kunshan High-tech Zone, Huaqiao Economic Development Zone Administrative Board, People's Governments of Townships, Municipal Water Resources Bureau, Municipal Environmental Protection Bureau and Municipal Water Affairs Group:

According to the recent data from the automatic water quality monitoring stations in Kunshan city, the water quality of several river segments used for national and provincial assessment is relatively poor. The situation is particularly severe for the Zhaotun water quality monitoring station (worse than Grade V), Zhengdong ferry station (worse than Grade V), and Qian Deng Pu Kou station (Grade V), all of which may fail to meet the national and provincial assessment requirements.

To ensure that the water quality in these river segments meets the annual national assessment requirement in 2018, we have decided to suspend the production of industrial enterprises (list attached) located near the Wusong River Basin Zhaotun (Shipu) water quality monitoring station and two other river basins near water quality monitoring stations, effective from December 25, 2017, to January 10, 2018. The suspension of production may be further extended, depending on the conditions of water quality readings. Relevant district and township governments should inform the enterprises about the decision. The inspection teams should supervise and take production cessation measures. Special investigators should be placed in the plants to ensure full compliance. Sluice gates along Wusong River, Taicang Embankment, and Qian Deng Pu must be closed, and the pumping facilities need to be shut down and stop discharging wastewater during this period. District and township governments and relevant departments shall ensure that enterprises take proper safety measures in the process of suspending and resuming production.

During the production suspension period, a daily reporting system will be adopted. The Municipal Water Resources Bureau shall inspect the status of all sluice gates and pumping facilities and report the inspection results to the City's "263" Office before 4:30 p.m. every day. District and township governments, special investigators based in the plants, and wastewater treatment plants shall check whether there are violations of the production suspension order and report the results to the Office (ks263bgs@163.com) before 4:30 p.m. every day.

Hereby noticed, and please follow the order.

Appendix: List of industrial enterprises that shall suspend production

The "263" Office of Kunshan Government

24th December, 2017

Notified Agencies: Municipal Office of Kunshan, Government Office of Kunshan

Copy to: Kunshan Safety Supervision Bureau, Kunshan City Fire Brigade

(Original Copy)

昆山市两减六治三提升专项行动领导小组办公室

昆 263 办〔2017〕186 号

关于对吴淞江赵屯（石浦）等 3 个断面所属流域工业企业实施全面停产的紧急通知

昆山开发区、昆山高新区、花桥经济开发区管委会，各镇人民政府，市水利局、环保局，水务集团：

近期我市自动监测数据显示，我市国省考断面水质较差，达标形势严峻，尤其是赵屯断面（劣V类）、振东渡口断面（劣 V 类）、千灯浦口断面（V类）均无法达到国省考要求。

为确保我市国省考断面达到国家下达 2018 年度考核目标要求，决定对吴淞江赵屯（石浦）等 3 个断面所属流域工业企业（企业名单附后）自 2017 年 12 月 25 日起至 2018 年 1 月 10 日期间实施全面停产，到期视水质情况，决定是否延期；请相关区镇通知相关企

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措施是否到位；对吴淞江、太仓塘、千灯浦沿线闸门全部关闭，泵站禁止排水；实施停产时、停产期间和复工复产时，请各区镇和相关部门督促企业落实好安全生产各项措施。

停产期间实施日报告制度，市水利局每日对站闸关闭情况、泵站排水情况进行检查，每日下午 4:30 前，将检查结果报市 263 办公室邮箱；各相关区镇每日对相关企业停产、网格员驻厂情况、所辖污水厂排放情况进行检查，每日下午 4:30 前将检查结果报市 263 办公室邮箱。（ks263bgs@163.com）

特此通知，请遵照执行。

附件：吴淞江赵屯（石浦）等 3 个断面所属流域停产企业名单

昆山市"两减六治三提升"专项行动领导小组办公室

2017 年 12 月 24 日

抄报：市委办、市府办。

抄送：市安监局、消防大队。

Appendix E. Threats to the Baseline Findings and Robustness Checks

In this section, we discuss a series of additional tests to address other potential threats to our baseline findings. Specifically, we show that the baseline findings are not driven by: (1) the endogenous location of monitoring stations; (2) the sorting of polluting firms; (3) spillover effects between upstream and downstream firms; (4) potential biases in the TFP measure; or (5) specific choices we make in the RD estimation.

A. Endogenous Location of Monitoring Stations

As discussed in Section II(A), the national water monitoring stations were established to reflect nationally representative information on water quality, and their locations were chosen based on hydrological (rather than economic) factors. Nevertheless, one may still be concerned about the endogeneity of monitoring station locations. For instance, a politically connected polluting firm might have strong incentives to lobby the government to locate the monitoring station in its upstream, so that it gets less stringent regulation. If these connected firms also receive other forms of benefits from the government that could affect their productivity, such as subsidies or loans, our RD estimates could be biased. In this section, we address this concern in two ways: an instrumental variable (IV) approach and a placebo test.

For the IV approach, we exploit the fact that, when monitoring stations were set up, local governments typically attempted to locate them close to existing hydrological stations, so that data, equipment, and technicians could be shared in order to achieve economies of scale.

A hydrological station collects hydraulic data such as water levels, flow velocity, flow direction, waves, sediment concentration, water temperature, and ice conditions, as well as data on meteorological conditions such as precipitation, evaporation, air temperature, humidity, air pressure, and wind. Because hydrological stations were set up between the 1950s and 1970s, a period when China barely had any industrial pollution at all, and because their locations were chosen based purely on hydrological considerations, their locations should be orthogonal to the future socio-economic conditions of their neighborhoods. In addition, all the hydrological stations were built and supervised by the Ministry of Water Resources (MWR), instead of the Ministry of Environmental Protection (MEP), and play no role in collecting any measures of water pollution.

Therefore, one would expect that, except for leading to the establishment of monitoring stations, the existence of a hydrological station alone should have minimal impact on the production and emission behaviors of adjacent firms. Utilizing this "exclusion restriction," we adopt "whether a firm is in the near upstream area of a hydrological station" as an instrumental variable (IV) for "whether a firm is in the near upstream area of a monitoring station," and estimate a 2SLS model to quantify the impacts of water quality monitoring on TFP.

Empirically, we estimate the following first-stage regression:

$$(4) \qquad UpMoni_{ijk} = \alpha \cdot UpHydro_{ijk} + \lambda_j + \sigma_\mathrm{k} + \epsilon_{ijk}$$

where $UpMoni_{ij}$ is a dummy variable indicating whether firm i in industry j is in the near upstream area (10 km) of monitoring station k; $UpHydro_{ijk}$ is a dummy variable indicating whether firm i in industry j is in the near upstream area (10 km) of a hydro-station k; λ_j and σ_k represent industry and monitoring site fixed effects; and ϵ_{ijk} is the error term. We then estimate the second stage regression:

$$(5) \qquad TFP_{ijk} = \alpha \cdot Up\widehat{Moni}_{ijk} + \lambda_j + \sigma_\mathrm{k} + \epsilon_{ijk}$$

where TFP_{ijk} is the TFP of firm i in industry j near the neighborhood of monitoring station k; $Up\widehat{Moni}_{ijk}$ is the predicted value from the first-stage regression; λ_j and σ_k are industry and monitoring site fixed effects; and ϵ_{ijk} is the error term.

The regression results are presented in Appendix Table S15. We estimate the effects separately for firms in polluting industries and non-polluting industries. First, we find that the locations of hydrological stations can strongly predict the locations of water quality monitoring stations (columns 1 and 3): if a firm is near the upstream of a hydrological station, it is also more likely to be in the near upstream of a monitoring station. The second-stage estimates show that being in the near upstream of a water monitoring station decreases the TFP of a polluting firm by 27% (column 2), but it does not affect the productivity of non-polluting firms (column 4).

Note that the regression results in Appendix Table S15 are not readily comparable to those in Table 1, as these two approaches use very different sources of variation in the data and estimate different treatment effects with different identifying assumptions. The RD design estimates the local average treatment effect at the cutoff, whereas the IV estimates the local average treatment effect for firms within 10-km bins around the hydrological stations. Nevertheless, the point estimates turn out to be highly consistent across these two different specifications: there exists a more than 25% gap in TFP in polluting industries and no significant TFP gap in non-polluting industries. Such consistency provides additional support for our baseline RD findings.

In addition to the IV approach, we conduct a placebo test to further demonstrate that the baseline findings are not driven by the endogenous location of monitoring stations. We obtained from the MEP a list of monitoring stations established between 2008 and 2012 and geocoded the locations of these stations. Since our ASIF sample is between 2000 and 2007, these "future (post-2008) monitoring stations" provide an ideal placebo test: if monitoring stations are indeed endogenously located based on TFP or emissions, then stations in the near upstream and downstream of "future stations" should already differ from each other even before 2007. As shown in Panel A of Appendix Table S16, we do not find any significant TFP gap between upstream and downstream firms near those "future stations," again suggesting that "endogenous station location" cannot explain our baseline RD findings.

B. Sorting of Polluting Firms

Another potential concern is that polluting firms might sort away from the near upstream of monitoring stations to avoid stringent regulation. If more productive upstream polluters are more willing (or able) to relocate, such endogenous sorting might confound the TFP gap between upstream and downstream polluters.

The results presented in Table 2 indicate that "endogenous firm sorting" is not the main driving force behind our baseline findings: when we exploit only within-firm variation in regulatory stringency for identification, which teases out the potential biases caused by endogenous firm sorting, the baseline treatment effects (Table 1) shrink by only a small (and statistically insignificant) margin. As discussed in Section V(C), the slight reduction in coefficient size is likely caused by attenuation bias after controlling for thousands of firm fixed effects.

To further investigate whether "endogenous sorting" affects our baseline findings in any substantial way, in this section, we conduct additional tests for the distribution of polluters across monitoring stations. First, we follow Cattaneo et al. (2018, 2019) and conduct a data-driven manipulation test. As shown in Panel A of Appendix Figure S2, using the baseline sample (collapsed cross-section of 2000-2007 data), we find that there is no discontinuity in the distribution of polluting firms around the monitoring stations. The formal statistical tests are summarized in Appendix Table S17. These results suggest that there does not exist any systematic sorting of polluting firms in our baseline sample.[39]

The intuition for the lack of sorting is the following: the firms in our ASIF dataset are generally large ones, for whom it is difficult and costly to relocate. Even if the firm wants to relocate, it needs to buy a new piece of land from another local government, and build a new factory, before it can move the labor and capital to the new site. For most large manufacturing firms, this whole process of relocation could take years to happen. Recall that in Figure 5, we found that environmental regulation became a

[39] Ideally, we would like to conduct the data-driven manipulation test for every industry. But for most industries, we do not have enough statistical power for this type of non-parametric exercise. Instead, we conduct simple balance tests for the number of firms in the near upstream and near downstream, for all the industries with at least 100 firms in our sample. As shown in Appendix Table S4, the composition of industries appears to be well balanced.

binding constraint only after 2003, while the sample ends in 2007. So, even if polluting firms decided to relocate immediately after regulation started to affect their production, the time window in our sample period is simply too short for that to happen, which explains why we could not detect any significant sorting in the data-driven manipulation test.

Fortunately, while we no longer have TFP information after 2007, the ASIF dataset still allows us to identify the location of polluting firms up until 2012, which is a decade after water quality monitoring started to matter for polluting firms.[40] To verify the intuition on the lack of sorting in the short run, we take the ASIF data in 2012 and re-run the same data-driven manipulation test. As shown in Panel B of Appendix Figure S2 , in 2012, the density of the polluting firms indeed gets less smooth at the cut-off: fewer polluting firms are located in the immediate upstream of monitoring stations, as compared to the immediate downstream. This pattern suggests that, in the long run, more polluting firms are leaving (or fewer polluting firms are being established in) the upstream regions to avoid tighter regulation. Combining the 2013 test with the pre-2007 test, we conclude that endogenous sorting only exists in the long run, so our baseline results are not confounded by endogenous sorting.

The data-driven manipulation tests are essentially comparing the density of polluting firms around the cut-off. One methodological concern is that, while the overall density remains unchanged, different types of polluting firms might differentially enter/exit the upstream and downstream areas, creating a confounding difference in the composition of firms. This concern, however, already has been addressed by our difference-in-discontinuities estimates in Table 2. As firm fixed effects are included in all these regressions, the upstream-downstream discontinuities in TFP are identified using within-firm variations, which should solely reflect the "intensive-margin" treatment effect, rather than any form of "sample selection" effect.

C. Spillover Effects

Another alternative interpretation of the baseline findings is that there might exist spillover effects between upstream and downstream polluters. For instance, if upstream and downstream firms directly compete with each other in the local input and output markets, then regulating upstream firms could cause positive spillovers to downstream firms, which makes the baseline RD result an overestimation of upstream firms' productivity loss due to regulation. When we extrapolate our baseline estimates to the whole country, the existence of such positive spillovers will also exaggerate the aggregate economic costs of improving water quality.

[40] The "value-added" variable is available in the ASIF dataset only until 2007; therefore, data in the later years could not be used for TFP analysis.

To assess whether potential spillover effects contribute to our findings in any substantial way, we conduct a placebo test where we compare "actual upstream firms" with "placebo downstream firms." Specifically, we first replace the actual downstream firms with their best matches from the sample of firms that are not in the neighborhood of any monitoring stations, based on the pre-2003 data. We then estimate the discontinuities between "actual upstream firms" and "placebo downstream firms" using the post-2003 data. Since the "placebo downstream firms" and "actual upstream firms" do not locate close to each other, this placebo regression teases out the potential spillover effects that might exist in the baseline regression. Therefore, if the spillover effects are driving the baseline RD findings, the placebo RD exercise should no longer detect any significant differences in TFP between actual upstream firms and placebo downstream firms.

In practice, we take the pre-2003 collapsed cross-sectional data, and for each downstream firm, we use the nearest neighbor matching strategy to find its best-matched firm from the pool of firms that are located at least 10 km away from the monitoring stations. By construction, these placebo downstream firms resemble the actual downstream firms in the pre-2003 period in terms of industry type, TFP, value-added, capital, labor, investment, loans, and ownership structure. We then replace the actual downstream firms by the placebo firms in the post-2003 sample and estimate the discontinuity between "actual upstream firms" and "placebo downstream firms."

The results are reported in Panel B of Appendix Table S16. We observe that the estimated coefficients are highly comparable to the baseline RD results, and are significantly larger than zero. This suggests that there exists no substantial spillover effect between upstream and downstream polluters, which could reflect the fact that the ASIF firms are large in magnitude, and thus mostly engage in the national and global markets rather than highly localized markets.

D. TFP Measure

In the baseline analysis, we rely on the Olley-Pakes approach to measure TFP, which assumes a monotonic relationship between a firm's investment and its productivity. In this section, we investigate the sensitivity of our findings with respect to this key assumption.

One potential concern is that tighter regulation might force upstream firms to invest more in abatement facilities, which is not caused by an increase in productivity, thus violating the monotonicity assumption. To deal with this issue, when estimating our baseline OP coefficients, we included "whether a polluter is in the near upstream of a monitoring station" as a state variable, which explicitly takes into account the abatement investments induced by tighter regulation.[41] To further address this concern, we also construct an alternative TFP measure where we drop all the upstream polluting firms when estimating the OP coefficients, so that "forced investments in the upstream" could no longer bias the OP estimates.[42] As shown in Panel A of Appendix Table S18, our baseline findings remain quantitatively the same with this alternative TFP measure, again suggesting that "forced investments in the upstream" is not the main driving force of the baseline results.

Another potential concern is that firm investments tend to be lumpy in general, which might break the monotonicity assumption and therefore bias the OP coefficients. "Lumpiness" could be a major issue in some developing-country datasets. For instance, more than 50% of the surveyed Chilean firms report zero investments (Levinsohn and Petrin, 2003). However, in the case of China's ASIF dataset, this issue is much less concerning: the investment variable appears to be of high quality, with only less than 1% of firms reporting zero investments in a given year (Brandt et al., 2012). Nevertheless, we construct several alternative TFP measures to directly address the "lumpy investments" concern.

First, we follow Olley and Pakes (1996) and drop all the incidents of zero investments in the ASIF data when estimating the OP coefficients. The results using this measure are shown in Panel B of Appendix Table S18.

Second, following Power (1998) and Nilsen and Schiantarelli (2003), we define "investment spikes" as incidents where a firm's investment in a given year exceeds 300% of its average value. We then exclude both "zero investment observations" and "investment spike observations" in the OP estimation, which gets rid of "lumpy investments" and keeps only "marginal investments" that are affected by year-to-year productivity shocks. In Panel C of Appendix Table S18, we replicate the baseline analysis with this alternative TFP measure.

Third, in addition to excluding incidents of "zero investments" and "investment spikes," we also follow Cooper et al. (1999) and define a variable called "capital age," which measures "the number of years elapsed since the firm's last investment spike." By including "capital age" as a state variable in the Olley-Pakes estimation, we further relax the monotonicity assumption needed for the OP coefficients to be consistent: in years with "smooth" investments (excluding zeros and spikes), conditional on the age of a firm's capital assets at the time, firm investment should be monotonic in

[41] After including this adjustment, the Olley-Pakes approach only requires the monotonicity assumption conditional on this state variable. Therefore, any break of monotonicity directly caused by regulation in the upstream will not bias the OP coefficients.

[42] The Olley-Pakes approach only requires investment to be monotonic in investment for a known subset of the data. So dropping the subsample that breaks monotonicity would in principle lead to consistent OP coefficients.

its productivity. In Panel D of Appendix Table S18, we replicate the baseline regressions using this alternative TFP measure.

Fourth, following Ackerberg et al. (2015), we further address the "lumpy investment" issue by using "intermediate input" instead of "investment" as the proxy variable (for unobserved productivity) to estimate the capital and labor coefficients for TFP construction. Since intermediate inputs are much less likely to be "lumpy," the monotonicity relationship (between the proxy variable and productivity) becomes more plausible under the Ackerberg et al. (2015) framework. The results using this alternative TFP measure are presented in Panel E of Appendix Table S18.

Fifth, instead of using the aforementioned "control function" approach to measure TFP, we follow Syverson (2011) and Greenstone et al. (2012) to construct a simple "index TFP" measure, where we assume a Cobb-Douglas production function, constant returns to scale, and no markups. Under these assumptions, the capital and labor coefficients are directly given by their respective cost/revenue shares, and TFP can in turn be obtained by calculating the residuals in value-added given the labor and capital parameters. The "index TFP" measure is transparent, and no longer assumes any monotonic relationship between a proxy variable (investment or intermediate input) and productivity. In Panel F of Appendix Table S18, we re-estimate the baseline RD models with the index TFP measure.

Finally, to show that our main results are not affected by the inclusion of the "upstream" state variable, in Panel G of Appendix Table S18, we also estimate the discontinuity with Olley-Pakes TFP that did not control for that state variable. As we can see, the results remain the same with this un-adjusted TFP measure.

Our baseline findings hold, both qualitatively and quantitatively, throughout Appendix Table S18. These robustness checks suggest that the TFP gap between upstream and downstream polluters cannot be explained by potential biases in the TFP measure itself. In Section VI, we will analyze the firm-level production and emission datasets in more detail to investigate the real channels behind our baseline findings.

E. Robustness to Different Specifications

We check the robustness of the baseline results in several ways. First, in Appendix Table S19, we estimate the RD using the parametric (global polynomial) approach. We experiment with linear, quadratic, and cubic functions of the running variable, and include different fixed effects in the regressions. We find similar results: water quality monitoring decreases polluting firms' TFP but has no impact on non-polluting firms.

In Panel A of Appendix Table S20, we follow the "bias-corrected" approach proposed by Calonico et al. (2014), where we estimate the baseline model using local quadratic regressions (instead of local linear regressions). With this alternative method, we obtain results that are quantitatively similar to the baseline.

In Panel B of Appendix Table S20, we use alternative bandwidth selectors. The bandwidth chosen in our main analysis is based on one common MSE (Mean Square Error)-optimal bandwidth selector for both sides across the cutoff. We supplement this analysis with five other types of bandwidth selectors: (1) MSE-two: two different MSE-optimal bandwidth selectors (below and above the cutoff) for the RD treatment effect estimator; (2) MSE-sum: one common MSE-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof); (3) CER (coverage error rate)-optimal: one common CER-optimal bandwidth selector for the RD treatment effect estimator; (4) CER-two: two different CER-optimal bandwidth selectors (below and above the cutoff) for the RD treatment effect estimator, and (5) CER-sum: one common CER-optimal bandwidth selector for the sum of regression estimates (as opposed to the difference thereof).[43] The results remain essentially the same regardless of the bandwidth selector being used.

In Panel C of Appendix Table S20, we conduct a placebo test using "fake" monitoring stations. We move the original stations upstream or downstream by 5 km and re-estimate the RD models. We find that the discontinuity in TFP is only evident at actual monitoring stations and not at these placebo stations.

[43] Please refer to Calonico et al. (2018) for technical details.

Appendix F. Link TFP Results to Emission Results

The firms in the ESR database together contribute 85% of China's total emissions, and all of them are local large emitters regardless of industry or revenues. Because we are unable to match the ESR firms with ASIF firms, we cannot directly link the TFP estimates with COD estimates without imposing additional assumptions.

In essence, the TFP and COD effects of water monitoring we estimated in previous tables are the following:

(1) $\mathrm{TFP_{ATE}}|\mathrm{Revenue} \geq 5 \text{ million} = \mathrm{E}(\mathrm{TFP_1} - \mathrm{TFP_0}|\mathrm{Revenue} \geq 5 \text{ million})$

(2) $\mathrm{COD_{ATE}}|\mathrm{COD} \geq \mathrm{x} = \mathrm{E}(\mathrm{COD_1} - \mathrm{COD_0}|\mathrm{COD} \geq \mathrm{x})$

where $\mathrm{TFP_{ATE}}|\mathrm{Revenue} \geq 5 \text{ million}$ is the average treatment effect of water quality monitoring on TFP for firms with annual revenues over 5 million yuan, and $\mathrm{COD_{ATE}}|\mathrm{COD} \geq \mathrm{x}$ is the average treatment effect of monitoring on emitters that produce COD pollution more than a given threshold x. $\mathrm{TFP_1}$ is the TFP for downstream firms, and $\mathrm{TFP_0}$ is the TFP for upstream firms.

The average treatment effects on TFP and COD over the entire distribution are:

(3) $\mathrm{TFP_{ATE}} = \mathrm{Prob}(\mathrm{Revenue} \geq 5 \text{ million}) \cdot \mathrm{TFP_{ATE}}|\mathrm{Revenue} \geq 5 \text{ million} + \mathrm{Prob}(\mathrm{Revenue} < 5 \text{ million}) \cdot \mathrm{TFP_{ATE}}|\mathrm{Revenue} < 5 \text{ million}$

(4) $\mathrm{COD_{ATE}} = \mathrm{Prob}(\mathrm{COD} \geq \mathrm{x}) \cdot \mathrm{COD_{ATE}}|\mathrm{COD} \geq \mathrm{x} + \mathrm{Prob}(\mathrm{COD} < \mathrm{x}) \cdot \mathrm{COD_{ATE}}|\mathrm{COD} < \mathrm{x}$

where the probabilities could be written as the share of firms appearing in each sample:

$$\mathrm{Prob}(\mathrm{Revenue} \geq 5 \text{ million}) = \frac{N_{ASIF}}{N},\ \mathrm{Prob}(\mathrm{Revenue} < 5 \text{ million}) = 1 - \frac{N_{ASIF}}{N};$$

$$\mathrm{Prob}(\mathrm{COD} \geq \mathrm{x}) = \frac{N_{ESR}}{N},\ \mathrm{Prob}(\mathrm{COD} < \mathrm{x}) = 1 - \frac{N_{ESR}}{N}.$$

While we cannot directly estimate "$\mathrm{TFP_{ATE}}|\mathrm{Revenue} < 5 \text{ million}$" and "$\mathrm{COD_{ATE}}|\mathrm{COD} < \mathrm{x}$" in the data, we attempt to back them out by extrapolating the intra-sample heterogeneous treatment effects on TFP and COD.

Recall that we find the Chinese government adopts the "Grasping the Large and Letting Go of the Small" strategy when implementing the water quality regulations. We explore two sets of additional heterogeneities related to firm size in Appendix Table S21. In Panel A, we estimate the heterogeneous treatment effects of water quality monitoring on TFP with respect to firms' revenues. In Panel B, we estimate the heterogeneous treatment effects on COD emission with respect to firms' total COD emissions. In both panels, we find that the effect of water quality monitoring is greater for big firms/emitters and is smaller and statistically insignificant for small firms/emitters, confirming small firms/emitters are less likely to be affected by water quality regulations.

In addition, in Appendix Table S22, we further explore whether "firm exit" is affected by water quality monitoring. In the ASIF data, there is an "exit" variable: if a firm earns less than 5 million Chinese yuan in a particular year, based on the sampling criteria, it will be dropped from ("exit") the database in the following year. This outcome provides additional information on whether water quality monitoring affects firms at the margin. The results in Appendix Table S22 show that the probability of exiting the ASIF database is not affected by water quality monitoring. This finding again shows that monitoring does not affect smaller firms.

Given these findings, we can assume the smaller firms/emitters are not affected by water quality monitoring and make the following extrapolations:

$$\mathrm{TFP}_{\mathrm{ATE}}|\mathrm{Revenue} < 5\ \mathrm{million} = 0 \tag{5}$$

$$\mathrm{COD}_{\mathrm{ATE}}|\mathrm{COD} < \mathrm{x} = 0$$

Intuitively, as the smallest producers and emitters in our ASIF or ESR dataset already have zero treatment effects, the even smaller producers and emitters (those excluded from the ASIF/ESR dataset) also should have zero treatment effects. We can therefore simplify Equations (3) and (4) to the following:

$$MRS = \frac{TFP_{ATE}}{COD_{ATE}} = \frac{N_{ASIF}}{N_{ESR}} \cdot \frac{\mathrm{TFP}_{\mathrm{ATE}}|\mathrm{Revenue}\geq 5\ \mathrm{million}}{\mathrm{COD}_{\mathrm{ATE}}|\mathrm{COD}\geq \mathrm{x}} \tag{6}$$

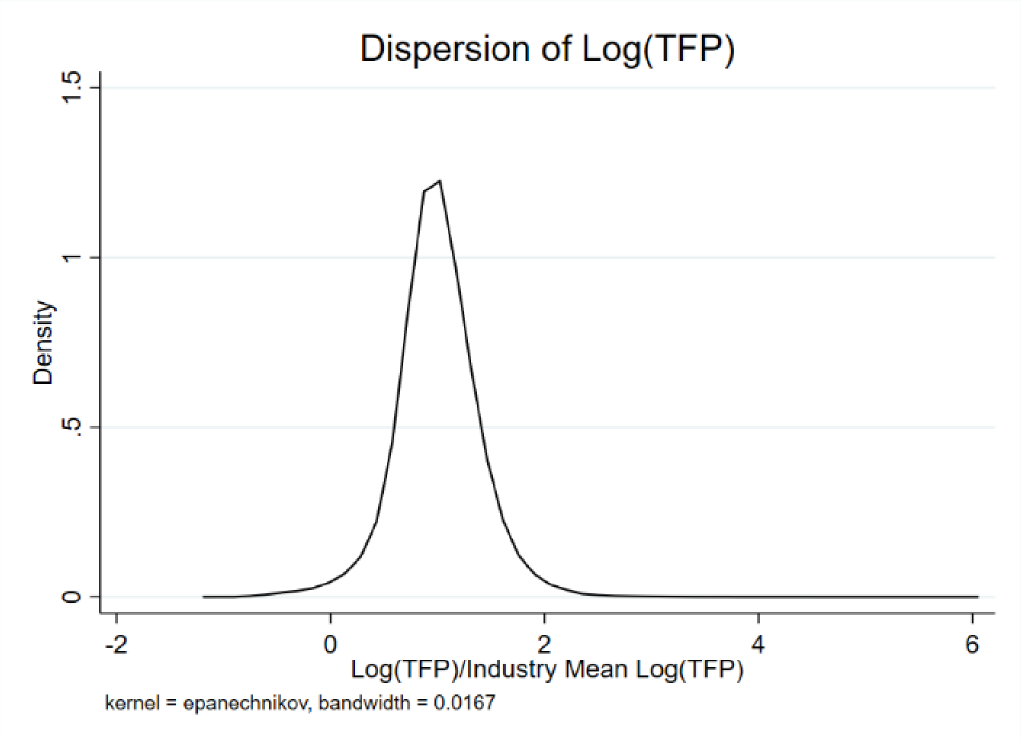
The sample we use for estimation includes 6,224 firms in polluting industries from the ASIF database and 9,797 polluters from the ESR database. Using this equation, we can calculate the economic costs of water pollution abatement.

The way we calculate the marginal impact of COD on productivity is analogous to the Wald estimator in the two-stage setting, except that we do not have a readily available tool to combine the two stages from two different samples non-parametrically and we need to adjust for sample size. We show that water quality monitoring reduced COD emissions by 0.84 logarithmic units and TFP by 0.36 logarithmic units, so a 10% change in COD emissions will lead to a (6,224/9,797)*(e^(-0.36)-1)/(e^(-0.84)-1)/10 = 3.38% change in TFP, where 6,224 is the number of polluting firms in the ASIF dataset and 9,797 is the number of firms in the ESR dataset. This estimate is reported in the first column of Panel A in Table 8.

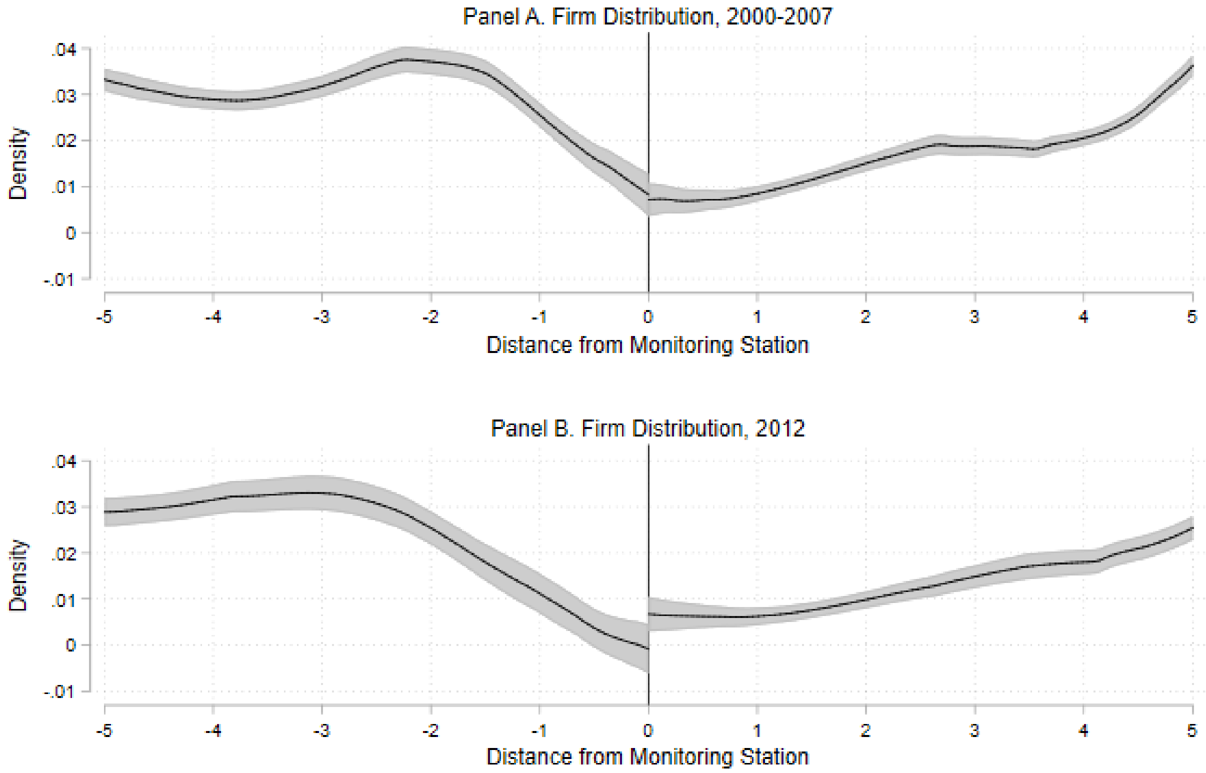
The next step is to quantify the economic cost caused by TFP reduction. Suppose in a given year the observed industrial value-added is Y and we also know that COD is reduced by 10%. As a 10% reduction in COD would cause a 3.38% reduction in TFP, the counterfactual value-added without abatement would be Y/(1-0.0338). The loss in industrial value-added can then be estimated by the difference between Y/(1-0.0338) and Y. We can apply the same method to data in different years and compute the corresponding loss in industrial value-added in different years (see Appendix Table S23 for details). Note that to apply this approach to the entire nation, we have to assume the marginal cost of abating COD to be linear and all the polluting firms are regulated in the same way as those being located near the water quality monitoring stations.

In the main calculation presented in our paper, we measure total COD reduction between 2000 and 2007 by assuming the 2000 COD emission level as the "counterfactual" for the 2001-2007 period. An alternative approach is to focus on the post-2003 period, and construct the counterfactual emissions by extrapolating based on the pre-2003 trend in COD emissions, which takes into account the fact that COD emission was already on a downward sloping trend before water quality readings became a political priority. For this alternative approach, we use a simple linear extrapolation to calculate the counterfactual COD emissions in the absence of additional regulation efforts, as shown in Appendix Figure S3. For each year after 2003, we then calculate the reduction in COD emissions relative to this extrapolated value and estimate the economic cost (measured by loss in industrial value-added) accordingly. Appendix Table S24 provides cost estimates under this alternative approach, and we can see the estimated economic cost of water regulation is roughly 40% of that presented in Table 8.

Appendix Figure S1. Dispersion of Log (TFP)

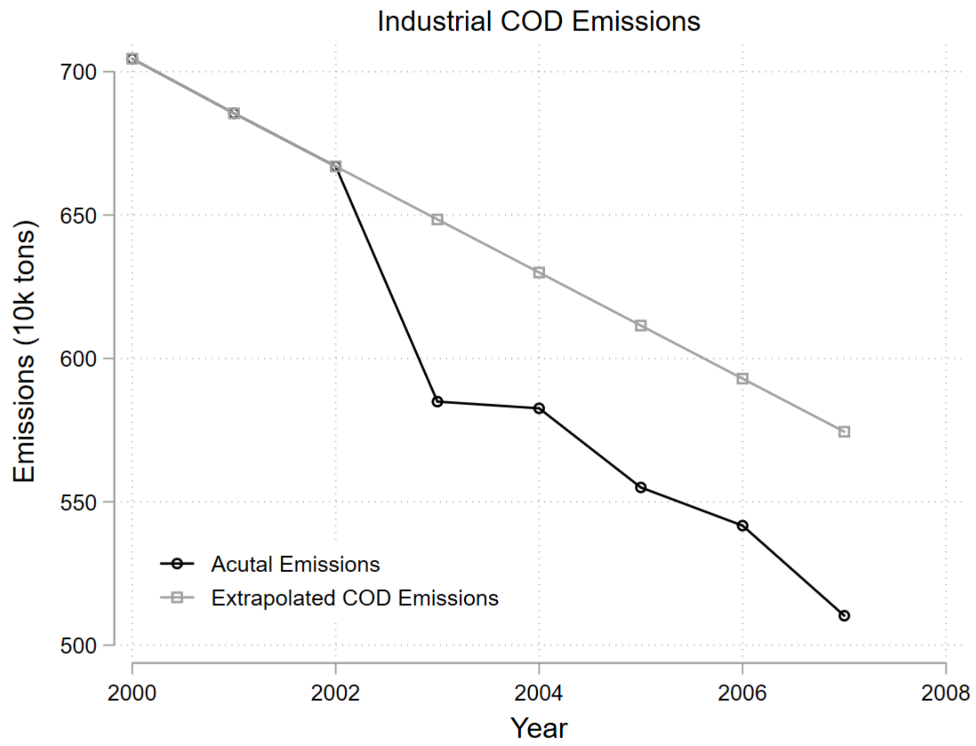


Appendix Figure S2. Distribution of Firms



Notes: This figure plots the density of polluting firms around the monitoring stations. Panel A shows that the density is continuous using data from 2000 to 2007. Panel B shows that there are fewer polluting firms just upstream of the monitoring stations in 2012.

Appendix Figure S3. Industrial COD Emissions and Counterfactual COD Emissions



Notes: The counterfactual COD emissions from 2003 to 2007 are based on a linear extrapolation of COD emission data from 2000 to 2002.

TableS1. Coefficients of Labor and Capital in Olley-Pakes TFP

Code	Industry Name	Capital Coef.	Labor Coef.
6	Mining and Washing of Coal	0.352	0.313
7	Extraction of Petroleum and Natural Gas	0.150	0.631
8	Mining and Processing of Ferrous	0.302	0.602
9	Mining and Processing of Non-Ferrous Metal Ores	0.411	0.532
10	Mining and Processing of Non-Metallic Mineral	0.394	0.603
13	Agricultural and Sideline Food	0.294	0.694
14	Food Manufacturing	0.344	0.721
15	Beverage Manufacturing	0.352	0.718
16	Tobacco Manufacturing	0.240	0.401
17	Textile Mills	0.275	0.572
18	Wearing Apparel and Clothing Accessories Manufacturing	0.304	0.552
19	Leather, Fur and Related Products Manufacturing	0.285	0.564
20	Wood and Bamboo Products Manufacturing	0.268	0.658
21	Furniture Manufacturing	0.324	0.672
22	Paper Products Manufacturing	0.332	0.668
23	Printing and Reproduction of Recorded Media	0.360	0.639
24	Education and Entertainment Articles Manufacturing	0.283	0.507
25	Petrochemicals Manufacturing	0.443	0.438
26	Chemical Products Manufacturing	0.364	0.586
27	Medical Goods Manufacturing	0.412	0.653
28	Chemical Fibers Manufacturing	0.254	0.574
29	Rubber Products Manufacturing	0.376	0.538
30	Plastic Products Manufacturing	0.368	0.492
31	Non-Metallic Mineral Products Manufacturing	0.343	0.575
32	Basic Metal Processing	0.335	0.695
33	Non-Ferrous Metal Processing	0.309	0.581
34	Fabricated Metal Products Manufacturing	0.365	0.553
35	General Purpose Machinery Manufacturing	0.348	0.595
36	Special Purpose Machinery Manufacturing	0.348	0.648
37	Transport Equipment Manufacturing	0.400	0.618
39	Electrical Equipment Manufacturing	0.351	0.551
40	Computers and Electronic Products Manufacturing	0.394	0.554
41	General Instruments and Other Equipment Manufacturing	0.338	0.561
42	Craftworks Manufacturing	0.291	0.498

Notes: This table reports the Olley-Pakes TFP Coefficients for Capital and Labor for different industries.

Table S2. Polluting vs Non-Polluting Industries

Polluting Industries		Non-Polluting Industries	
Industry	Code	Industry	Code
Mining and Washing of Coal	6	Forestry	2
Mining and Processing of Ferrous Metal Ores	8	Extraction of Petroleum and Natural Gas	7
Mining and Processing of Non-metallic Mineral	10	Mining and Processing of Non-Ferrous Metal Ores	9
Fermentation	14 (6)	Agricultural and Sideline Food Processing	13
Beverage Manufacturing	15	Food Manufacturing	14
Textile Mills	17	Tobacco Manufacturing	16
Leather, Fur and Related Products Manufacturing	19	Wearing Apparel and Clothing Accessories Manufacturing	18
Pulp and Paper Manufacturing	22 (1, 2)	Wood and Bamboo Products Manufacturing	20
Petrochemicals Manufacturing	25	Furniture Manufacturing	21
Chemical Products Manufacturing	26	Paper Products Manufacturing	22
Medicine Manufacturing	27 (1, 2, 4)	Printing and Reproduction of Recorded Media	23
Chemical Fibers Manufacturing	28	Education and Entertainment Articles Manufacturing	24
Non-Metallic Mineral Products Manufacturing	31	Medical Goods Manufacturing	27
Iron and Steel Smelting	32 (1, 2)	Rubber Products Manufacturing	29
Non-Ferrous Metal Smelting	33 (1)	Plastic Products Manufacturing	30
Fossil-Fuel Power Station	44 (1)	Basic Metal Processing	32
		Non-Ferrous Metal Processing	33
		Fabricated Metal Products Manufacturing	34
		General Purpose Machinery Manufacturing	35
		Special Purpose Machinery Manufacturing	36
		Transport Equipment Manufacturing	37
		Electrical Equipment Manufacturing	39
		Computers and Electronic Products Manufacturing	40
		General Instruments and Other Equipment Manufacturing	41
		Craftworks Manufacturing	42
		Renewable Materials Recovery	43
		Electricity and Heat Supply	44
		Gas Production and Supply	45
		Water Production and Supply	46

Notes: Industrial classification for national economic activities (GB/T 4754—2002). The division between polluting industries and non-polluting industries is according to the MEP (http://wfs.mep.gov.cn/gywrfz/hbhc/zcfg/201009/t20100914_194483.htm).

Table S3. Covariate Balance Between Upstream and Downstream Firms

	Mean		Mean Difference
	Downstream	Upstream	⩽5km
	(1)	(2)	(3)
Panel A. Time-Invariant Factors			
Year of Opening	1986	1985	0.49
	(15)	(16)	(3.59)
SOE	0.18	0.21	0.01
(1=Yes, 0=Others)	(0.39)	(0.41)	(0.07)
Polluting Firm	0.36	0.35	-0.02
(1=Yes, 0=No)	(0.48)	(0.48)	(0.04)
Panel B. Pre-2003 Firm-Level Characteristics			
TFP	3.01	2.96	0.05
(log)	(1.59)	(1.63)	(0.21)
Profit	1.18	1.20	0.68
(million yuan)	(3.91)	(4.46)	(0.51)
Value Added	8.46	8.48	-0.07
(log)	(1.16)	(1.20)	(0.19)
# of Employee	8.83	8.92	-0.02
(log)	(1.60)	(1.63)	(0.34)
Capital Stock 1	4.95	5.01	0.02
(log)	(1.05)	(1.09)	(0.22)
Intermediate Input	9.47	9.49	-0.03
(log)	(1.20)	(1.24)	(0.22)

Notes: Columns 1–2 report the means and standard deviations of firm characteristics. In columns 3, we test the covariate balance between upstream and downstream firms. The difference coefficients are obtained by running OLS regressions of firm characteristics on an upstream dummy, industry fixed effects, and water quality monitoring station fixed effects. TFP is estimated using the Olley and Pakes (1996) method, with "upstream polluting" added as an additional state variable. Standard errors reported in the parentheses are clustered at the water monitoring station level.

Table S4. Upstream and Downstream Industry Balances

	Mean		Mean Difference
	Downstream	Upstream	⩽10km
	(1)	(2)	(3)
Agricultural and Sideline Food Processing	0.067	0.052	-0.015
Ind. Code: 13	(0.251)	(0.222)	(0.012)
Food Manu.	0.031	0.024	-0.007
Ind. Code: 14	(0.174)	(0.153)	(0.006)
Textile Mills	0.056	0.056	0.000
Ind. Code: 17	(0.230)	(0.230)	(0.010)
Wearing Apparel and Clothing Accessories Manu.	0.037	0.045	0.008
Ind. Code: 18	(0.189)	(0.208)	(0.010)
Paper Products Manu.	0.032	0.027	-0.005
Ind. Code: 22	(0.177)	(0.163)	(0.008)
Printing and Reproduction of Recorded Media	0.047	0.031	-0.016
Ind. Code: 23	(0.211)	(0.173)	(0.019)
Chemical Products Manu.	0.070	0.076	0.006
Ind. Code: 26	(0.256)	(0.265)	(0.013)
Plastic Products Manu.	0.040	0.049	0.009
Ind. Code: 30	(0.196)	(0.217)	(0.013)
Non-Metallic Mineral Products Manu.	0.123	0.093	-0.029
Ind. Code: 31	(0.328)	(0.291)	(0.024)
Fabricated Metal Products Manu.	0.047	0.051	0.005
Ind. Code: 34	(0.211)	(0.221)	(0.012)
General Purpose Machinery Manu.	0.072	0.054	-0.018
Ind. Code: 35	(0.259)	(0.226)	(0.012)
Special Purpose Machinery Manu.	0.047	0.060	0.013
Ind. Code: 36	(0.213)	(0.238)	(0.010)
Transport Equipment Manu.	0.044	0.047	0.004
Ind. Code: 37	(0.204)	(0.212)	(0.009)
Electrical Equipment Manu.	0.063	0.045	-0.018*
Ind. Code: 39	(0.242)	(0.206)	(0.011)
Computers and Electronic Products Manu.	0.032	0.056	0.024
Ind. Code: 40	(0.177)	(0.230)	(0.015)

Notes: Columns 1–2 report the means and standard deviations of firm characteristics. In column 3, we test the covariate balance between upstream and downstream firms. The difference coefficients are obtained by running OLS regressions of industry indicators (two-digit) on an upstream dummy. We focus on industries with at least 100 firms in the sample in 2000. Standard errors reported in the parentheses are clustered at the water monitoring station level.

Table S5. Covariate Balance between Upstream and Downstream Townships

	Mean		Mean Difference
	Downstream	Upstream	⩽10km
	(1)	(2)	(3)
Panel A. Basic Township Characteristics			
Town Area	8.78	8.71	-0.07
(Mu, Log)	(0.60)	(0.68)	(0.07)
Arable Area	7.82	7.55	-0.20*
(Mu, Log)	(0.96)	(1.14)	(0.12)
Distance to County Center	1.16	1.19	0.02
(KM, Log)	(0.30)	(0.32)	(0.05)
Old-Region Town	0.21	0.16	-0.03
(1=Old-Region Town)	(0.41)	(0.36)	(0.04)
Minority Town	0.01	0.02	-0.01
(1=Minority Town)	(0.12)	(0.15)	(0.02)
No. of Residents Communities	0.49	0.49	-0.08
(Log)	(0.80)	(0.71)	(0.13)
No. of Villages	3.10	2.96	-0.07
(Log)	(0.71)	(0.63)	(0.08)
Panel B. Basic Infrastructure			
Road Length	3.66	3.50	-0.02
(KM, Log)	(0.90)	(0.80)	(0.12)
# of Villages with Paved Road	3.04	2.93	-0.07
(Log)	(0.72)	(0.63)	(0.08)
# of Villages with Electricity	3.10	2.96	-0.07
(Log)	(0.71)	(0.63)	(0.08)
# of Villages with Tap Water	2.06	1.78	-0.12
(Log)	(1.29)	(1.18)	(0.17)
Panel C. Human Capital			
# of Primary Schools	2.81	2.75	-0.03
(Log)	(0.57)	(0.54)	(0.07)
# of Primary School Students	8.66	8.49	-0.08
(Log)	(0.73)	(0.68)	(0.10)

Notes: Data are collected from the Township Conditions Survey in 2002. Columns 1–2 report the means and standard deviations of township covariates. In column 3, we test the covariate balance between upstream and downstream towns. The difference coefficients are obtained by running OLS regressions of township variables on an upstream dummy and water quality monitoring station fixed effects. Standard errors reported in the parentheses are clustered at the water monitoring station level.

Table S6. Summary Statistics of Several Other Variables

	Mean	Std. Dev.
Panel A. Emissions in the ESR Database		
COD Emissions	8.05	2.53
NH3-N Emissions	3.01	3.31
Wastewater Discharge	10.11	2.36
SO2 Emissions	9.61	2.02
NOx Emissions	8.99	1.94
Panel B. Production Measures in the ESR Database		
Operating Hours	3,339	1,102
Water Usage (log)	11.47	2.34
# of Wastewater Treatment Facility	1.26	4.95
Wastewater Treatment Capacity (tons/day)	3,458	22,129
Panel C. Other Variables in the ASIF Database Used in the Paper		
Emission Fee (available only in 2004, log)	0.97	1.57
Strongly Incentivized Leader (=1 if the Party Secretary <56)	0.67	0.47
Automatic Stations (=1 if Automatic)	0.16	0.37
Large Firm (=1 if # of Employee >50)	0.70	0.46
SNWD (=1if Affected by the SNWD project)	0.14	0.34

Notes: Summary statistics are calculated based on ASIF and ESR data from 2000 to 2007.

Table S7. Difference-in-Discontinuities and Difference-in-Differences Estimates

	TFP		
	(1)	(2)	(3)
Panel A. Diff-in-Disc Estimates			
Difference in Discontinuities (Polluting*Downstream)	0.28**	0.29**	0.41***
	(0.13)	(0.14)	(0.16)
Station FE Absorbed	Y	Y	Y
Industry FE Absorbed	Y	Y	Y
Bandwidth (km)	5.96	5.35	5.05
Kernel	Triangle	Epanech.	Uniform
Panel B. Diff-in-Diff Estimates			
DID Estimates (Polluting*Downstream)	-0.03	0.17**	0.33**
	(0.04)	(0.08)	(0.13)
Station FE Absorbed	Y	Y	Y
Industry FE Absorbed	Y	Y	Y
Bandwidth (km)	10	5.0	2.5

Notes: Panel A and Panel B report the "difference in discontinuities" estimates: the difference between "polluting firms' upstream-downstream TFP discontinuity" and "non-polluting firms' upstream-downstream TFP discontinuity." Panel C reports the "difference in differences" estimate: the difference between "polluting firms' upstream-downstream TFP mean difference" and "non-polluting firms' upstream-downstream TFP mean difference. "TFP is estimated using the Olley and Pakes (1996) method, with "upstream polluting" added as an additional state variable. The discontinuities at monitoring stations are estimated using local linear regressions and MSE-optimal bandwidth proposed by Calonico et al. (2014) and Calonico (2017) for different kernel weighting methods. * significant at 10% ** significant at 5% *** significant at 1%.

Table S8. Water Quality Monitoring and TFP: Year by Year RD

	Polluting Industries			Non-Polluting Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Before and After 2003						
Before 2003	0.02	-0.00	0.05	-0.02	-0.06	-0.10
	(0.26)	(0.26)	(0.30)	(0.14)	(0.14)	(0.13)
Obs.	2,278	2,278	2,278	4,132	4,132	4,132
After 2003	0.39**	0.44**	0.37**	0.09	0.08	0.08
	(0.19)	(0.19)	(0.17)	(0.07)	(0.08)	(0.11)
Obs.	5,306	5,306	5,306	10,017	10,017	10,017
Panel B. by Year						
Year 2000	-0.00	0.06	0.00	-0.26	-0.18	-0.16
	(0.27)	(0.29)	(0.35)	(0.18)	(0.21)	(0.22)
Obs.	1,229	1,229	1,229	2,154	2,154	2,154
Year 2001	-0.10	-0.06	-0.08	-0.17	-0.14	-0.14
	(0.29)	(0.28)	(0.29)	(0.20)	(0.21)	(0.22)
Obs.	1,653	1,653	1,653	2,921	2,921	2,921
Year 2002	0.12	0.13	0.03	0.09	0.08	0.02
	(0.25)	(0.25)	(0.29)	(0.18)	(0.18)	(0.16)
Obs.	1,856	1,856	1,856	3,288	3,288	3,288
Year 2003	0.48**	0.59**	0.48**	0.09	0.07	0.05
	(0.20)	(0.27)	(0.24)	(0.16)	(0.16)	(0.15)
Obs.	2,121	2,121	2,121	3,484	3,484	3,484
Year 2004	0.39*	0.45	0.50	0.07	0.03	-0.04
	(0.22)	(0.31)	(0.31)	(0.14)	(0.13)	(0.12)
Obs.	2,986	2,986	2,986	5,034	5,034	5,034
Year 2005	0.48*	0.55**	0.44**	-0.06	-0.09	-0.03
	(0.26)	(0.27)	(0.22)	(0.17)	(0.17)	(0.18)
Obs.	3,323	3,323	3,323	5,830	5,830	5,830
Year 2006	0.56**	0.63**	0.55*	-0.05	-0.05	-0.07
	(0.25)	(0.29)	(0.30)	(0.15)	(0.14)	(0.13)
Obs.	3,702	3,702	3,702	6,488	6,488	6,488
Year 2007	0.46*	0.48*	0.51*	0.14	0.15	0.12
	(0.26)	(0.27)	(0.29)	(0.09)	(0.10)	(0.10)
Obs.	4,140	4,140	4,140	7,449	7,449	7,449
Station FE Absorbed	Y	Y	Y	Y	Y	Y
Ind. FE Absorbed	Y	Y	Y	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher TFP than upstream firms. TFP is estimated using the Olley and Pakes (1996) method, with "upstream polluting" added as an additional state variable. Local linear regression and MSE-optimal bandwidth proposed by Calonico et al. (2014) and Calonico (2017) for different kernel weighting methods are used for the estimation. Conventional local linear regression discontinuity standard errors clustered at the monitoring station level are reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Table S9. Water Quality Monitoring and TFP: Difference in Discontinuities Estimates

	Polluting Industries			Non-Polluting Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Compare RD between the 2000-2001 period and the 2002 period						
Downstream*Post2002	-0.00	0.01	0.01	0.01	-0.01	0.02
	(0.11)	(0.11)	(0.11)	(0.07)	(0.06)	(0.06)
Panel B: Compare RD between the 2000 period and the 2001- 2002 period						
Downstream*Post2001	-0.09	-0.08	-0.06	0.03	0.02	0.04
	(0.11)	(0.11)	(0.11)	(0.06)	(0.06)	(0.06)
Firm FE Absorbed	Y	Y	Y	Y	Y	Y
Station-by-Year FE Absorbed	Y	Y	Y	Y	Y	Y
Industry-by-Year FE Absorbed	Y	Y	Y	Y	Y	Y
Obs.	4,368	4,368	4,368	6,324	6,324	6,324
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate "difference in discontinuities" estimate: the difference between "TFP discontinuity before the cutoff year" and "TFP discontinuity after the cutoff year." The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher TFP than upstream firms. TFP is estimated using the Olley and Pakes (1996) method, with "upstream polluting" added as an additional state variable. The discontinuities at monitoring stations are estimated using local linear regressions and MSE-optimal bandwidth proposed by Calonico et al. (2014) and Calonico (2017) for different kernel weighting methods. * significant at 10% ** significant at 5% *** significant at 1%.

Table S10. Difference in Discontinuities Estimates for Value Added, Labor, and Capital Stock

	Value Added (log)			Capital Stock (log)			Employees (log)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Difference in Discontinuities	0.07	0.08	0.09	-0.21***	-0.23***	-0.26***	-0.05	-0.06	-0.06
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)	(0.05)	(0.05)	(0.05)
Firm FE Absorbed	Y	Y	Y	Y	Y	Y	Y	Y	Y
Station-by-Year FE Absorbed	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-by-Year FE Absorbed	Y	Y	Y	Y	Y	Y	Y	Y	Y
Obs.	11,578	11,578	11,578	11,578	11,578	11,578	11,578	11,578	11,578
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate Difference-in-Discontinuities estimate: difference bettween pre-2003 upstream-downstream discontinuity and post-2003 upstream-downstream discontinuity. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher "Y" than upstream firms.Standard errors are clustered at the monitoring station level, and reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Table S11. Water Quality Monitoring and TFP: Heterogeneity by Emission Intensity

	Low Emission Intensity			High Emission Intensity		
	(1)	(2)	(3)	(4)	(5)	(6)
RD in COD (log)	-0.27	-0.35	-0.39	1.03**	1.06**	0.91**
	(0.31)	(0.31)	(0.33)	(0.49)	(0.51)	(0.46)
Obs.	4,558	4,558	4,558	4,548	4,548	4,548
Firm FE Absorbed	Y	Y	Y	Y	Y	Y
Industry FE Absorbed	Y	Y	Y	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher COD emissions than upstream firms. In columns 1–3, we report the estimated discontinuity for low-emission intensity firms, and in columns 4–6, we report the estimated discontinuity for high-emission intensity firms. Local linear regression and MSE-optimal bandwidth proposed by Calonico et al. (2014) and Calonico (2017) for different kernel weighting methods are used for the estimation. * significant at 10% ** significant at 5% *** significant at 1%.

Table S12. Water Quality Change and TFP

	TFP (log)	
	(1)	(2)
Water Quality	0.05	
	(0.05)	
Upstream*Water Quality	0.08	0.07
	(0.07)	(0.10)
Polluting*Water Quality	0.11	0.16
	(0.14)	(0.14)
Upstream*Polluting*Water Quality	-0.26*	-0.31**
	(0.13)	(0.15)
Firm FE Absorbed	Y	Y
Industry FE*Year FE Absorbed	Y	Y
Station FE*Year FE Absorbed		Y
Observations	8,984	8,739
R-squared	0.93	0.94

Notes: This table reports the impacts of monitoring station water quality readings on the productivity of upstream and downstream polluting firms. The sample consists of ASIF firms located within 4km of each monitoring station. Water quality readings are collected from environmental yearbooks and measured on a scale of 1 to 6. In column 1, we control for Firm FE and Industry-by-Year FE. In column 2, we further control for Station-by-Year FE. In both specifications, the improvement of water quality reading significantly hurts the TFP of polluting firms in its upstream, but not other adjacent firms. The triple interaction term's negative coefficients indicate that upstream firms have lower TFP than upstream firms. Standard errors clustered at the monitoring station level are reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Table S13. Robustness Check: Political Incentives and Regulation Stringency

	TFP (log)	
	(1)	(2)
Diff-in-Discontinuities	0.22*	0.27**
(Political Incentive*Downstream)	(0.11)	(0.12)
Firm FE Absorbed	Y	Y
Year FE Absorbed	Y	Y
Leader FE Absorbed		Y
Observations	11,810	11,023

Notes: This table reports the robustness of the "promotion incentive" results to the inclusion of politician fixed effects. Column 1 presents the baseline coefficients under this specification, column 2 adds the political incentive dummy and its interaction with the downstream dummy. Standard errors clustered at the monitoring station level are reported below the estimates. * significant at 10% ** significant at 5% *** significant at 1%.

Table S14. Capital Difference in the Medium Run

	Long-Run Capital Difference (Log)		
	(1)	(2)	(3)
RD Estimates	-0.46**	-0.47*	-0.54**
	(0.23)	(0.24)	(0.26)
Station by Industry FE Absorbed	Y	Y	Y
Sample	2008-2012	2008-2012	2008-2012
Obs	5,075	5,075	5,075
Kernel	Triangle	Epanech.	Uniform

Notes: This table summarizes the discontinuities in capital stock between upstream and downstream firms. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The negative coefficients indicate that downstream firms have lower capital stock than upstream firms. Local linear regression and MSE-optimal bandwidth proposed by Calnoico et al. (2014) and Calonico (2017) for different kernel weighting methods are used for the estimation. Standard errors are clustered at the monitoring station level, and reported below the estimates.* significant at 10% ** significant at 5% *** significant at 1%.

Table S15. Instrumental Variable Estimation using Hydrological Stations

	Polluting Industries		Non–Polluting Industries	
	Upstream	TFP (log)	Upstream	TFP (log)
	(1)	(2)	(3)	(4)
Upstream Hydrological Station	0.30***		0.30***	
	(0.10)		(0.09)	
Upstream Monitoring Station		-0.31*		-0.01
		(0.17)		(0.13)
Specification	1st Stage	2SLS	1st Stage	2SLS
Station FE Absorbed	Y	Y	Y	Y
Industry FE Absorbed	Y	Y	Y	Y
Observations	6,307	5,969	11,534	11,527
F Statistic	10.48	0.03	22.82	1.18
R-squared	0.46	0.45	0.43	0.23

Notes: Each column in the table represents a separate regression. We define "upstream monitoring station" as a dummy indicator for whether a firm is upstream from a monitoring station within a 10 km range, and similarly, we define "upstream hydrological station" as a dummy indicator for whether a firm is upstream from a hydrological station within a 10 km range. TFP is estimated using the Olley and Pakes (1996) method, with "upstream polluting" added as an additional state variable. The instrumental variable is "upstream hydrological station." We present first-stage results and IV 2SLS results separately for firms in polluting industries (columns 1 and 2) and firms in non-polluting industries (columns 3 and 4). The negative coefficient in column 2 indicates that upstream firms lower TFP than downstream firms. Monitoring station fixed effects are controlled for in all specifications. Standard errors are clustered at the monitoring station level. * significant at 10% ** significant at 5% *** significant at 1%.

Table S16. RD Estimates using Placebo Firms and Monitoring Stations

	Polluting Industries			Non-Polluting Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Water Monitoring Stations Built in 2012						
TFP (log)	-0.03	-0.12	-0.11	0.01	0.00	-0.05
	(0.43)	(0.42)	(0.32)	(0.15)	(0.15)	(0.16)
Obs.	6,268	6,268	6,268	15,452	15,452	15,452
Panel B. RD Estimates using Placebo Downstream Firms						
TFP (log)	0.33*	0.33*	0.30*	0.05	0.03	0.04
	(0.19)	(0.19)	(0.17)	(0.11)	(0.11)	(0.10)
Obs.	3,997	3,997	3,997	7,923	7,923	7,923
Station FE Absorbed	Y	Y	Y	Y	Y	Y
Industry FE Absorbed	Y	Y	Y	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher TFP than upstream firms. TFP is estimated using the Olley and Pakes (1996) method, with "upstream polluting" added as an additional state variable. In Panel A, we estimate the TFP discontinuity across water quality monitoring stations that were established in 2012. In Panel B, we replace each downstream firm by its best match in the whole ASIF database using nearest neighbor matching based on pre-2003 characteristics (industry type, TFP, value-added, capital, labor, investment, loans, and ownership). Then we estimate the discontinuities between upstream firms and replaced downstream firms. In all regressions, TFP is estimated using Olley and Pakes (1996) method. The discontinuities at monitoring stations are estimated using local linear regression and MSE-optimal bandwidth proposed by Calonico et al. (2014) and Calonico (2017) for different kernel weighting methods. Standard errors clustered at the monitoring station level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table S17. Density Tests for Sorting Using Local Polynomial Density Estimation

	Firms 2000-2007		Firms 2012	
	(1)	(2)	(3)	(4)
T	-0.77	-0.34	2.58	2.27
P>|T|	0.44	0.73	0.01	0.02
Bandwidth Left	2.43	2.16	2.89	2.62
Bandwidth Right	2.52	2.16	3.02	2.62
Obs	6,311	6,311	2,611	2,611
Bandwidth Selector	Each	Diff	Each	Diff

Notes: This table reports RD manipulating tests using the local polynomial density estimators proposed by Cattaneo et al. (2017a, 2007b). Two different bandwidth selectors are used to test the density discontinuity. "Each" means we use two distinct bandwidths based on MSE of each density separately for upstream and downstream firms. "Diff" bandwidth selection is based on MSE of the difference of densities with one common bandwidth. Technical explanations can be found in Cattaneo et al. (2017a, 2007b).

Table S18. RD Estimates using Alternative TFP Measures

	TFP (log)		
	(1)	(2)	(3)
Panel A: Exclude Upstream Polluting Firms in OP Estimation			
RD in TFP (log)	0.32**	0.33**	0.26
	(0.16)	(0.16)	(0.17)
Panel B: Drop "Zero Investment"			
RD in TFP (log)	0.38	0.44*	0.39*
	(0.24)	(0.25)	(0.23)
Panel C: Drop "Zero Investments" and "Investment Spikes"			
RD in TFP (log)	0.39*	0.44**	0.42**
	(0.20)	(0.21)	(0.20)
Panel D: Drop "Zero Investments" and Control for "Capital age"			
RD in TFP (log)	0.30*	0.31**	0.39*
	(0.15)	(0.15)	(0.21)
Panel E: Use Intermediate Input as the "Proxy Variable"			
RD in Log TFP (ACF Approach)	0.31**	0.31**	0.36**
	(0.13)	(0.13)	(0.15)
Panel F: Use Capital and Labor Cost Shares as Elasticities in C-D function			
RD in Log TFP (Index Approach)	0.39***	0.42***	0.38**
	(0.15)	(0.15)	(0.19)
Panel G: TFP Olley-Pakes: No State Variable			
RD in Log TFP	0.37**	0.37**	0.37**
	(0.18)	(0.18)	(0.18)
Station FE Absorbed	Y	Y	Y
Industry FE Absorbed	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate regression. In Panel A, we exclude all the upstream polluting firms in the OP estimation process, to show that "regulation breaking down OP assumptions" could not drive the main findings. In Panel B, we follow the OP Method (Olley and Pakes, 1996) to estimate TFP, and exclude all the observations with zero investment in the estimation process, following the original OP paper to address the "lumpy investment" issues. In Panel C, we use the OP method, excluding both "zero investments" and "investment spikes" (defined following Power (1998) and Cooper et al. (1995)) in the estimation process, to further address the "lumpy investment" issues. In Panel D, in addition to dropping "zero investments," we control for "capital age" (time elapsed since last investment spike as defined by Power (1998) and Cooper et al. (1995)) as a state variable in the OP estimation process, to further address the "lumpy investment" issues. In Panel E, we use the ACF approach (Ackerberg et al., 2015) for TFP estimation, which uses "intermediate inputs" as the "proxy variable" to solve the "lumpy investment" issues, to show that our findings can not be driven by lumpy investments. In Table F, we use the "index method" to estimate TFP (Greenstone et al., 2012), which does not rely on strict monotonicity assumptions as the OP approach, to show that lumpy investments cannot explain the findings.

Table S19. Water Quality Monitoring and TFP: Polynomial RD Estimates

	TFP (log)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Polluting Industries						
RD in TFP (log)	0.25***	0.34**	0.48**	0.22**	0.32**	0.44**
	(0.10)	(0.15)	(0.22)	(0.10)	(0.15)	(0.21)
Obs.	5,965	5,965	5,965	5,643	5,643	5,643
R-Square	0.46	0.46	0.46	0.54	0.54	0.54
Panel B. Non-Polluting Industries						
RD in TFP (log)	0.08	0.12	0.13	0.09	0.13	0.13
	(0.09)	(0.12)	(0.14)	(0.09)	(0.11)	(0.14)
Obs.	11,522	11,522	11,522	10,961	10,961	11,522
R-Square	0.23	0.23	0.23	0.33	0.33	0.23
Polynomial Function	Linear	Quadratic	Cubic	Linear	Quadratic	Cubic
Station FE	Y	Y	Y			
Industry FE	Y	Y	Y			
Station by Industry FE				Y	Y	Y

*Notes:*Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher TFP than upstream firms.We report OLS estimates of the coefficient on a "downstream" dummy after controlling for polynomial functions in distance from the water quality monitoring stations interacted with a downstream dummy. Standard errors clustered at the monitoring station level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table S20. Robustness Checks: Water Quality Monitoring and TFP

	TFP – Polluting Industries		
	(1)	(2)	(3)
Panel A. Correct Bias Caused by Small Bandwidth			
Bias-corrected RD Estimates	0.25*	0.27*	0.29**
	(0.15)	(0.15)	(0.14)
Panel B. Alternative Ways to Choose Optimal Bandwidth			
Bandwidth Chosen by MSE-Two Selector	0.31*	0.39**	0.35**
	(0.17)	(0.18)	(0.16)
Bandwidth Chosen by MSE-Sum Selector	0.34*	0.39**	0.35**
	(0.19)	(0.20)	(0.15)
Bandwidth Chosen by CER-D Selector	0.34*	0.39**	0.44**
	(0.19)	(0.20)	(0.19)
Bandwidth Chosen by CER-Two Selector	0.24	0.33*	0.40**
	(0.18)	(0.19)	(0.19)
Bandwidth Chosen by CER-Sum Selector	0.25	0.32	0.44**
	(0.20)	(0.21)	(0.19)
Panel C. Placebo Tests			
Move Monitoring Stations Upstream by 5km	0.12	0.11	0.09
	(0.16)	(0.16)	(0.17)
Move Monitoring Stations Downstream by 5km	0.01	0.03	0.08
	(0.10)	(0.10)	(0.11)
Station FE Absorbed	Y	Y	Y
Industry FE Absorbed	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher TFP than upstream firms. In Panel A, we report bias-corrected RD estimates. In Panel B, we use alternative bandwidth selectors proposed by Calonico et al. (2014) and Calonico (2017). In Panel C, we conduct placebo tests by moving monitoring stations upstream/downstream by 5km. * significant at 10% ** significant at 5% *** significant at 1%.

Table S21. Water Quality Monitoring and TFP: Emission Heterogeneity by Size

	Small Firms/Emitters			Large Firms/Emitters		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: RD Estimates for TFP (log)						
RD in TFP (log)	0.27	0.30	0.23	0.50**	0.58***	0.47**
	(0.19)	(0.20)	(0.21)	(0.19)	(0.22)	(0.22)
Obs.	2,699	2,699	2,699	3,158	3,158	3,158
Panel B: RD estimates for COD Emission (log)						
RD in COD (log)	0.55	0.52	0.29	1.21*	1.21*	1.28*
	(0.51)	(0.56)	(0.38)	(0.68)	(0.69)	(0.73)
Obs.	4,795	4,795	4,795	4,896	4,896	4,896
Firm FE Absorbed	Y	Y	Y	Y	Y	Y
Industry FE Absorbed	Y	Y	Y	Y	Y	Y
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms have higher TFP (COD emissions) than upstream firms. In columns 1–3, we report the estimated discontinuity for smaller firms or emitters, and in columns 4–6, we report the estimated discontinuity for large firms or emitters. Local linear regression and MSE-optimal bandwidth proposed by Calonico et al. (2014) and Calonico (2017) for different kernel weighting methods are used for the estimation. * significant at 10% ** significant at 5% *** significant at 1%.

Table S22. Water Quality Monitoring and Firm Exit

	Polluting Industries			Non-Polluting Industries		
	(1)	(2)	(3)	(4)	(5)	(6)
RD in Firm Exit	0.04	0.04	0.09	0.00	0.00	-0.01
	(0.09)	(0.09)	(0.10)	(0.05)	(0.05)	(0.05)
Obs.	6,202	6,202	6,202	11,459	11,459	11,459
Station FE Absorbed	Y	Y	Y	Y	Y	Y
Industry FE Absorbed	Y	Y	Y	Y	Y	Y
Kernel	Epanech.	Triangle	Uniform	Epanech.	Triangle	Uniform

Notes: Each cell in the table represents a separate RD regression. The running variable is the distance between a firm and a monitoring station, where negative (positive) distance means firms are located to the upstream (downstream) of the monitoring stations. The positive coefficients indicate that downstream firms are more likely to exit the ASIF database than upstream firms. The discontinuities at monitoring stations are estimated using local linear regression and MSE-optimal bandwidth proposed by Calonico et al. (2014) and Calonico (2017) for different kernel weighting methods. Standard errors clustered at the monitoring station level are reported below the coefficients. * significant at 10% ** significant at 5% *** significant at 1%.

Table S23. Estimated Economic Cost: An Example

Year	Industrial COD Emissions	Reduction (%)	Industrial VA (100 million Y)	Polluting Firms' VA (100 million Y)	TFP loss per 1% COD	TFP loss in that year	VA loss (100 million Y)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
2000	704.50	0.00%	40259	$15,862			
2001	685.48	2.70%	43854	$17,279	0.338%	0.009	159
2002	666.97	5.33%	47775	$18,823	0.338%	0.018	345
2003	584.93	16.97%	55362	$21,813	0.338%	0.057	1327
2004	582.59	17.30%	65775	$25,915	0.338%	0.058	1610
2005	555.00	21.22%	77958	$30,716	0.338%	0.072	2373
2006	541.68	23.11%	92236	$36,341	0.338%	0.078	3079
2007	510.26	27.57%	111691	$44,006	0.338%	0.093	4522
00-07 Sum (100 million Y)							**13415**

Notes: This table illustrates how we calculate the economic loss due to COD abatement. We first calculate the reduction in COD relative to 2000 for each year between 2001 and 2007 (columns 1 and 2). We then estimate the TFP loss due to this reduction based on the baseline results reported in the first column of Panel B in Table 1 and Panel A in Table 5. The final step is to estimate the loss in industrial value-added based on actual industrial value-added data in different years. COD emission data are collected from China's Environmental Yearbooks. Industrial value-added data are collected from the National Bureau of Statistics' website.

Table S24. Alternative Estimates on the Economic Costs of COD Abatement

	Cross-Section RD			Within-Firm RD		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. MRS between TFP Loss and COD Reduction						
TFP Loss per 10% COD Emission Abatement	3.38%	3.81%	3.53%	2.12%	2.28%	2.22%
Panel B. Estimated Costs for all Polluting Firms from 2003 to 2007						
Total Loss in Industrial VA from 2003 to 2007 (billion CNY)	523	592	548	324	349	340
Kernel	Triangle	Epanech.	Uniform	Triangle	Epanech.	Uniform

Notes: This table calculates the loss in industrial VA from 2003 to 2007. We assume that without tighter political-incentive driven policies, the COD emissions would follow the same trend as the 2000 to 2002 period. We can then calculate the reduction in COD emissions in each year from 2003 to 2007 based on the counterfactual emissions and actual emissions. Panel B report the total loss in industrial VA based on this alternative assumption. More details can be found in Appendix F.

APPENDIX REFERENCES

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