WATERING DOWN ENVIRONMENTAL REGULATION IN CHINA*

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This article 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 data sets, 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 with their immediate downstream counterparts. We find that the discontinuity in TFP does not exist in nonpolluting 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 were associated with an economic cost of more than 800 billion Chinese yuan. *JEL* Codes: Q56, Q58, O13, O44, D24.

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

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(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 United States, which sheds limited light on the developing world, where the cost of environmental regulation might vary substantially because of 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 article 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 several 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 immediately upstream of monitoring stations, as compared with 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 compared with 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 nonpolluting industries and is predominantly caused by upstream polluters investing more heavily in (nonproductive) abatement equipment and making costly adjustments to clean up production processes.[1]

1. Intuitively, investments in "abatement equipment" and "cleaner production process" are important capital inputs for firms, but they do not lead to increases

To put the magnitude of our findings in context, the estimated upstream–downstream TFP gap is comparable to two years of average TFP growth for Chinese manufacturers during our sample period (2000–2007),[2] and a back-of-the-envelope calculation for the whole country suggests that water regulation cost more than 110 billion Chinese yuan a 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 "noncontractable" 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:

i. The upstream–downstream gap only emerged immediately after 2003, when the central government started to link water quality readings to political promotions.
ii. The upstream–downstream gap is predominantly driven by prefectural cities with politically motivated leaders,

in output. The regulated firms are producing less output for a given amount of inputs, and therefore have lower TFP. We formalize this intuition with a simple model in Online Appendix A and use it to guide the empirical investigation.

2. With the same data set and same method for TFP estimation, Brandt, Van Biesebroeck, and Zhang (2012) find 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 multitasking (Holmstrom and Milgrom 1991; Hart, Shleifer, and Vishny 1997).

and there is no significant spatial discontinuity when the local leaders do not have promotion prospects.

iii. Only polluters within a few kilometers upstream are regulated, as emissions from farther upstream would dissipate quickly over space and have negligible effect on water quality readings.

iv. 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.

v. 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.

Our article 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. Although there exists a large body of 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, 2013; Ryan 2012; Kahn and Mansur 2013), they have focused almost exclusively on developed countries. In sharp contrast, little systematic knowledge exists on the environment–economy trade-off 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]

4. Two studies are closely related to ours: Cai, Chen, and Gong (2016) documents that Chinese provinces have incentives to "pollute their neighbors" by allowing the furthest downstream counties to engage in more water-polluting production activities; Lin and Sun (2020) shows that the establishment of automatic water monitoring stations hurts upstream water-polluting industries. Our paper complements these two studies by causally identifying the "intensive margin"

Second, our article 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 overcentralization 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). This article complements this conventional wisdom by showing that such central–local alignment might break down in the presence of imperfect performance monitoring. In addition, this article 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 2016; Jia 2017) by shedding light on how China's environmental regulations are implemented at the local level.

Third, because of data and identification challenges, the literature on environmental regulation has mainly focused on air pollution, whereas water pollution remains underresearched, 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 effects of water regulation on production activities. To fill in this gap, our study investigates the effects of water regulation on 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 the article is structured as follows. Section II describes the institutional background and research design.

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.

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

II.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% 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 began 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. Under this system, water monitoring stations were built to collect various measures of water pollution in all the major river segments, lakes, and reservoirs in China and 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 local government officials.[5] The monitoring network was thus considered to serve mostly scientific rather than regulatory purposes, and

5. In the 9th Five-Year Plan (1996–2000), no explicit goals for emission reduction and water quality readings were mentioned.

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 on existing hydrological stations.[6]

In 2002, Hu Jintao took over the presidency from Jiang Zemin. Given the country's mounting environmental challenges, Hu began 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 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%

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

7. The SOD is generally regarded as 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.

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): (i) reducing COD emissions by 10%; (ii) ensuring that by 2010, no more than 22% of monitored water sections would fail to meet Grade V National Surface Water Quality Standards; and (iii) ensuring that at least 43% of the monitored water sections (of the seven main bodies of water in China) would meet Grade III National Surface Water Quality Standards by 2010.[10]

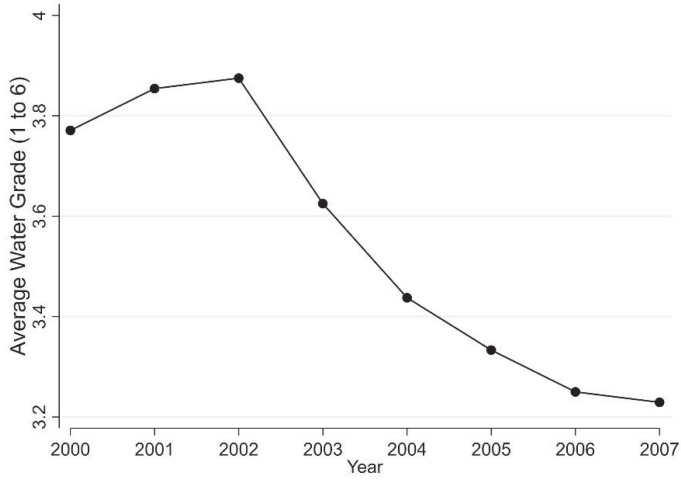
To meet these targets, the central government assigned abatement requirements to each province, and provincial governors were required to sign individual responsibility contracts with the central government, documenting their emission abatement plans and commitments in detail. Provincial governors further 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, because 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 Online 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. Although 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 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 Online Appendix A.

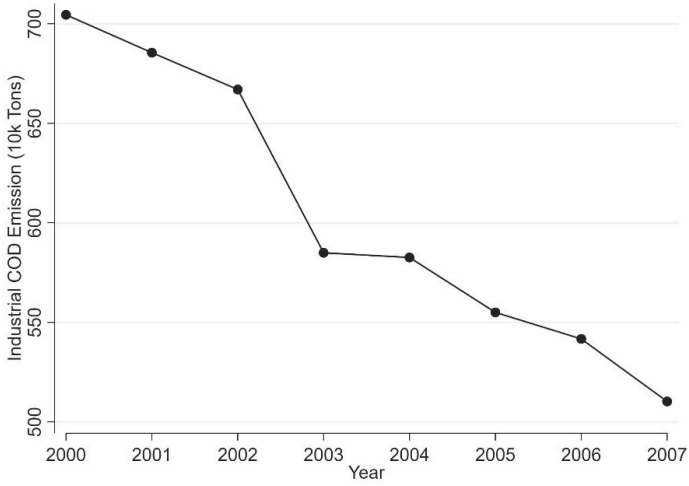
Under the local officials' efforts to regulate polluting firms and abate water pollution, China's surface water quality improved dramatically after 2003. In Figure I, Panel A, we plot the

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

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



(A) Water Quality from 2000 to 2007



(B) Industrial COD Emissions from 2000 to 2007

FIGURE I

Water Quality and COD Emission

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 and 6 represents lowest water quality. Panel B shows the trend of national industrial COD emissions.

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 emphasizing 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 Figure I, Panel B, we also plot the yearly national industrial COD emissions between 2000 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.

II.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

11. The overall surface water quality in China is graded on a six-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.

have lower productivity than adjacent downstream firms. This empirical strategy is related in spirit to recent work exploiting the flow of pollution along rivers for identification (Lipscomb and Mobarak 2016; Keiser and Shapiro 2019a), but is novel in that it uses 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 differ from each other later as upstream firms face tighter regulation. As discussed in the introduction, 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 nonparametric 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:

$$(1) \qquad TFP_{ijk} = \alpha_1 Down_{ijk} + \alpha_2 Dist_{ijk} + \alpha_3 Down_{ijk} \cdot Dist_{ijk} + u_j + v_k + \varepsilon_{ijk} \qquad s.t. \; -h \leqslant Dist_{ijk} \leqslant h,$$

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 nonparametric estimations, we control for industry and monitoring station fixed effects u_j and v_k in the baseline

model. The estimation of this nonparametric 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 nonparametric estimations on the residualized TFP.[12]

We augment the baseline econometric specification in several different ways: (i) controlling for industry-by-station fixed effects; (ii) 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; (iii) combining polluting and nonpolluting industries in a unified model and directly estimating the heterogeneous treatment effect; and (iv) 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

III.A. Data

In this article, we combine several novel data sets that provide comprehensive information on the socioeconomic conditions of townships, production and performance of industrial firms, and emissions from heavy polluters centered around water monitoring stations.

1. Water Quality Monitoring Stations. We collect information on water quality monitoring stations from surface water quality reports in various environmental yearbooks from 1999 to 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,

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.

ranging from 400 to 500 stations. We geocoded all the water quality monitoring stations.[13]

2. 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 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 are 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 drop observations with missing key financial indicators or with negative values for value-added, employment, and the capital stock. We 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 0.5th to 99.5th 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 multiunit 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. Although there are various approaches to measure TFP, it

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 firm address cannot be precisely geocoded.

has been documented in the literature that these measures are in general highly correlated with each other (Syverson 2011). Here we rely on the semiparametric estimator suggested by Olley and Pakes (1996) to construct our baseline TFP measure, which addresses the simultaneity and 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 to 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 Online Appendix C. The estimated labor and capital coefficients for each industry are reported in Online Appendix Table S1.

The ASIF firms can be categorized into polluting industries and nonpolluting 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 use 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.

3. 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

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

comprehensive environmental data in China and 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.

For every firm included in the ESR data set, 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, 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

17. Among the handful of economic studies focusing on water quality, Sigman (2002) and Lipscomb and Mobarak (2016) use biochemical oxygen demand (BOD); Duflo et al. (2013) use BOD and COD (and several other indicators); and Keiser and Shapiro (2019a) focus on "dissolved oxygen" and whether water is safe for fishing.

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 other measures of water pollution: ammonia-nitrogen (NH_3-N) emissions and wastewater discharge.

4. Township-Level Socioeconomic Data. The National Bureau of Statistics conducts the Township Conditions Survey 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 these survey data for 20 provinces in 2002 and use the township-level data to assess similarities between upstream and downstream townships.

5. 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 data sets are then matched to our geocoded township and firm data sets.

III.B. Data Matching

To the best of our knowledge, the data we have compiled are 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 overlapping 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, making it difficult to define upstream and

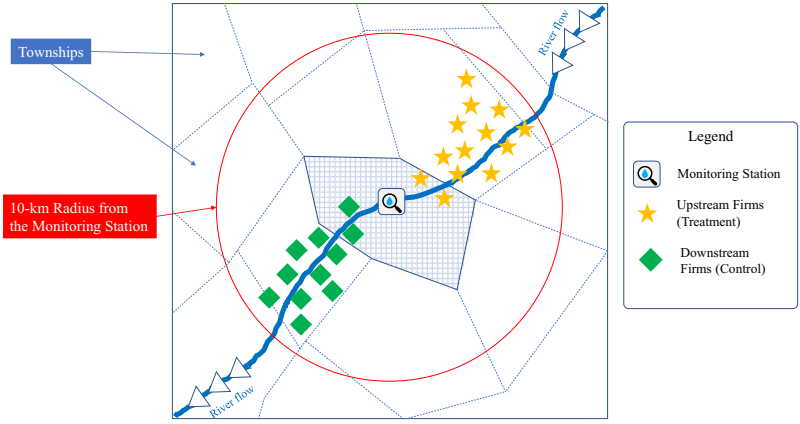


FIGURE II

Illustrating the Identification Strategy

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.

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 data set. 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 data sets. We also drop these monitoring stations from our sample. After these exclusions, we are left with 159 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, which are located around 159 water quality monitoring stations.

We attempted to match the firms across the ASIF and ESR samples. However, because these two data sets use different

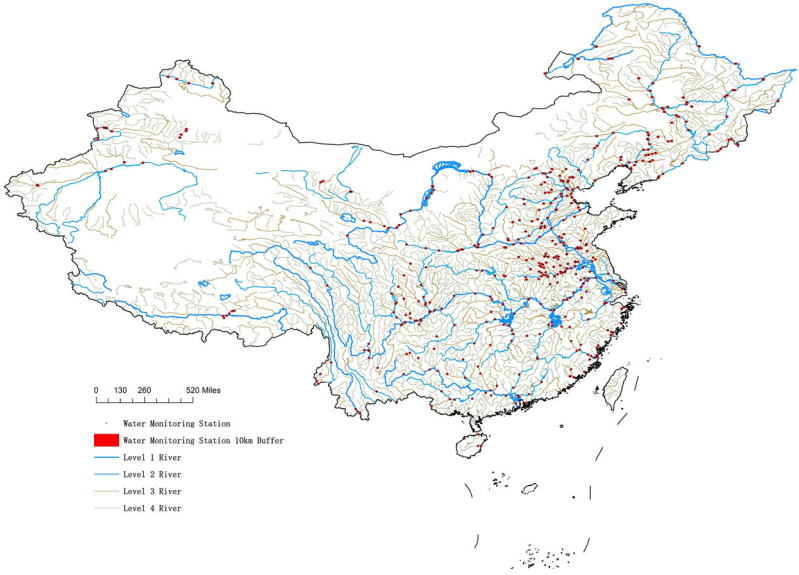


FIGURE III

Distribution of Surface Water Quality Monitoring Stations in China

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 article, we analyze the data sets separately.

III.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 Online Appendix, documenting that upstream and downstream firms/townships are similar along time-invariant and predetermined dimensions, as well as along time-varying dimensions before water quality regulation became effective in 2003.

In Online Appendix Table S3, we present the summary statistics and balance checks for firm-level characteristics. In the ASIF data set, 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 Hu came into power in 2003; thus, water monitoring stations should not affect upstream firms in the pre-2003 period of our data.[18] In Online Appendix Table S3, Panel B, 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 Online Appendix Table S4, we further test whether different industries are balanced across the monitoring stations. We focus on two-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 conduct balance tests using township-level data and report our findings in Online 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.

The results in Online Appendix Tables S3–S5 are encouraging, as they indicate that upstream and downstream firms are similar for time-invariant characteristics and pre-2003 covariates, and these firms are located in townships that are highly comparable. Although 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]

18. The dynamic analysis of the RD results are 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.

20. In Online Appendix Table S6, we also report the summary statistics for the other variables used in the article.

IV. Baseline Results

IV.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 fixed effects and industry fixed effects) 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 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 (<5 km) 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 effects 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 nonpolluting industries.

Table I quantifies the graphical findings in Figure IV. Panel A presents the RD estimates without any controls, for both polluting and nonpolluting 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 nonpolluting 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 159 water quality monitoring stations in 34 manufacturing industries. A nonsaturated RD regression, as reported in Panel A, would compare upstream and downstream firms from 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

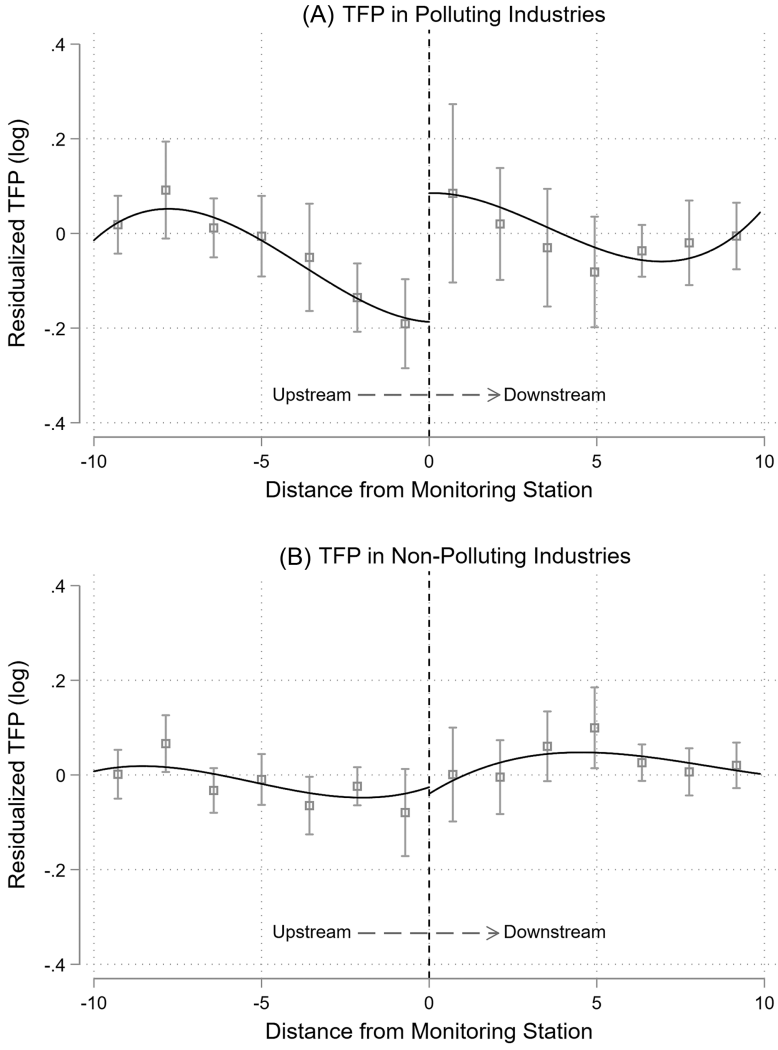


FIGURE IV

RD Plot: Effects of Water Quality Monitoring on TFP

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

TABLE I

THE UPSTREAM–DOWNSTREAM TFP GAP

	Polluting industries			Nonpolluting 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, and 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%.

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 effects are quantitatively similar across these 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 nonpolluting 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 in 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, whereas there exists no such discontinuity in nonpolluting 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 fewer 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 toward 0 (Pischke 2007).[21]

Although 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 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.

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 split 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.

To make the comparison between polluting and nonpolluting industries in Table I more explicit, we adopt two alternative econometric specifications. Specifically, we pool the data for the polluting and nonpolluting firms together, and directly estimate the difference between "the TFP gap in polluting industries" and "the TFP gap in nonpolluting 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 nonparametric RD model while interacting every term with a dummy variable indicating "polluting industries." As can be seen in Online Appendix Table S7, Panel A, 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 nonpolluting industries. As shown in Online Appendix Table S7, Panel B, 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 toward 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.

IV.B. Dynamic Effects

As discussed in 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 hypothesize that the TFP gap between upstream and downstream polluters should become salient after 2003. To

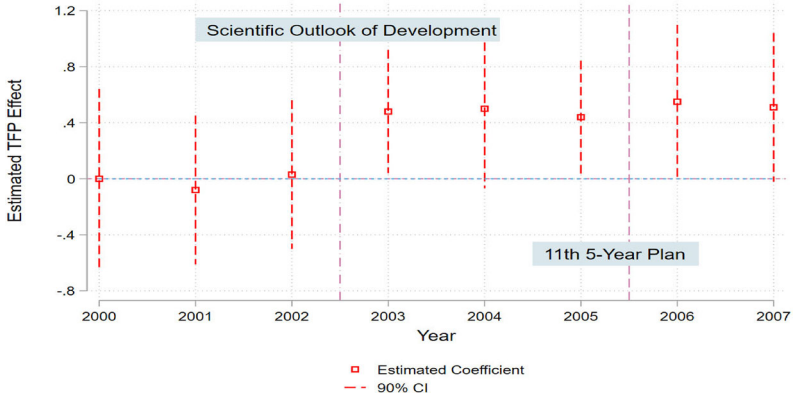


FIGURE V

RD Estimates by Year

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.

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 Online Appendix Table S8. In the same table, we replicate the exercise for nonpolluting 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 because 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 versus downstream firms or polluting versus nonpolluting industries, but also to the timing of environmental policies in China during our sample period.

IV.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 (2018), we use a "bias-corrected" approach to estimate the following model:[22]

$$\begin{aligned}\overline{TFP_{ijkt}} = {} & \alpha_1 Down_{ijk} + f(Dist_{ijk}) + Down_{ijk} \cdot f(Dist_{ijk}) + \alpha_2 Down_{ijk} \cdot Post03_t \\ & + f(Dist_{ijk}) \cdot Post03_t + Down_{ijk} \cdot f(Dist_{ijk}) \cdot Post03_t + \varepsilon_{ijkt} \\ & s.t. -h \leqslant Dist_{ijk} \leqslant h \end{aligned} \tag{2}$$

where $Post03_t$ is a dummy variable that equals 1 if $t \geqslant 2003$, 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 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, compared with their downstream counterparts. In comparison, as shown in columns (4)–(6), there is no such break in trends between upstream and downstream nonpolluters.

The estimated treatment effect for upstream polluters is slightly smaller than the baseline results presented in Table I, which is probably 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

22. The reported estimates are based on local quadratic regressions. Local linear regressions also yield similar findings.

TABLE II

THE UPSTREAM–DOWNSTREAM TFP GAP: DIFFERENCE IN DISCONTINUITIES ESTIMATES

	Polluting industries			Nonpolluting industries		
	(1)	(2)	(3)	(4)	(5)	(6)
Downstream * Post-2003	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)	10.39	10.20	9.89	8.96	8.87	9.17
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-absorbed from TFP through an OLS regression. The discontinuities at monitoring stations are estimated using local linear regressions and MSE-optimal bandwidth proposed by Calonico, Cattaneo, and 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%.

to endogenous locational choices, such bias could at most account for only a small proportion of the baseline findings.

In Online 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.

IV.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 nonpolluting 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 Online Appendix E. Specifically, we show that the baseline RD results are not driven by (i) the endogenous location of monitoring stations, (ii) the sorting of polluting firms, (iii) spillover effects between upstream and downstream firms, (iv) potential biases in our baseline TFP measure, or (v) specific choices we make in the RD estimation.

First, we address the potentially 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 on the existing hydrological network. The hydrological stations were set up between the 1950s and 1970s when China had very little 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 effect on the production and emission behaviors of adjacent firms. Using 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 Online 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 compare 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 because the firms in our ASIF data set are generally large, 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 Online 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 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 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 Online 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: (i) we estimate different versions of Olley-Pakes TFP excluding incidents of "zero investments" and "investment spikes," and controlling for "capital age"; (ii) 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 (iii) we follow Syverson (2011) and Greenstone, List, and Syverson (2012) to construct a simple "index TFP" measure, which also does not rely on the monotonic relationship between investment and productivity. As discussed in Online Appendix E, our baseline findings hold, both qualitatively and quantitatively, for all these alternative TFP measures.

Finally, in Online Appendix E, we present a series of additional robustness checks, including estimating parametric RD models, bias-correcting the RD estimates following Calonico, Cattaneo, and Titiunik (2014), and adopting alternative bandwidth selectors. All the main findings remain quantitatively similar throughout these alternative specifications. We conduct a placebo test by moving the original monitoring stations upstream

or downstream by 5 km and reestimating 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? We examine the channels through which environmental regulation affects firms' TFP. The theoretical framework that guides our analysis is presented in Online 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 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 effects of water quality monitoring on several key variables: (i) input and output measures that constitute TFP; (ii) emission reduction efforts at both the production and the abatement stages; and (iii) final emission outcomes.

V.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 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, we focus on input-related measures: labor, capital, and intermediate inputs. We find that upstream polluting firms hire more employees and use slightly more intermediate inputs, but these effects are statistically insignificant. The most salient pattern is that upstream polluting firms, although 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 (nonproductive) equipment to cope with tighter environmental regulation.

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	− 0.22	− 0.19	− 0.09	− 0.07	0.01	0.05
(log)	(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	− 0.05	− 0.04	− 0.05	− 0.03	− 0.01	0.05
input (log)	(0.24)	(0.24)	(0.18)	(0.16)	(0.16)	(0.20)
Panel C: Single factor productivity (downstream minus upstream)						
RD in (VA/employee)	0.08	0.08	0.05	0.00	0.02	0.01
(log)	(0.08)	(0.08)	(0.08)	(0.06)	(0.06)	(0.05)
RD in (VA/capital stock)	0.25**	0.27***	0.28***	0.04	0.04	− 0.00
(log)	(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, and 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%.

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 Table III, Panel C, 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 Table III, columns (4)–(6), 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 Online Appendix Table S10, the upstream polluters started to own higher amounts of capital assets after 2003, confirming the findings in Table III.

V.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 were 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 use detailed information on abatement strategies documented in the firm-level emission data set 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 to improve water quality readings, firms located in the near upstream of monitoring stations have to reduce their production time

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, and 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%.

by nearly 5% compared with 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 Table IV, Panels C and D, 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 a day.[23]

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 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 TFP among upstream polluting firms.

V.C. Emission Abatement Outcomes

The model in Online 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 effects of water quality monitoring on firm emissions and emission intensity.

We examine eight pollution outcome measures from the ESR data set: (i) total amount of COD emitted; (ii) COD emission intensity $\left(\frac{\text{total COD}}{\text{total output value}}\right)$; (iii) total amount of nitrogen ammonia (NH_3-N) emitted; (iv) NH_3-N emission intensity $\left(\frac{\text{total } NH_3\text{-N}}{\text{total output value}}\right)$; (v) total amount of wastewater discharged; (vi) wastewater discharge intensity $\left(\frac{\text{total wastewater}}{\text{total output value}}\right)$; (vii) SO_2 emissions; and (viii) 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 $e^{-0.84} - 1$).

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

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: NH_3-N emissions (downstream minus upstream)			
RD in NH_3-N emissions (log)	0.87	0.76	0.46
	(0.90)	(0.76)	(0.62)
RD in NH_3-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 SO_2 emissions (log)	0.03	0.06	−0.16
	(0.29)	(0.30)	(0.25)
RD in NO_x 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, and 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%.

As discussed in more detail in Online 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 Online 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 Table V, Panel B, 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, because 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 NH_3-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 consistently suggest that upstream polluters have much lower NH_3-N emission intensity than do 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 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 in 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 data set with the ASIF data set, 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.[24] We estimate a difference-in-differences-in-differences (DDD) model, investigating whether monitoring stations experiencing larger water quality improvements also see larger upstream–downstream TFP gaps in that year. As shown in Online 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 in 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 because of 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 with their near downstream counterparts. These findings are supported by abundant qualitative evidence summarized in Online Appendix D, in which

24. We thank a referee for suggesting this test.

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 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 analyses. Next we present three pieces of evidence showing that the political incentives of local politicians are indeed the driving forces behind our main findings. Then we investigate how the regulatory burdens are shared among different types of firms, which shed further light on the incentives of local government officials.

VI.A. Political Economy of Regulation Enforcement

In Table VI, Panel A, we provide evidence that local governments hold double standards in environmental regulation for upstream versus downstream firms. In the ASIF data set, 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 because of 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. This implies that local governments are able to charge firms differentiated emission fee rates, even though these firms are located close to each other and are in the same administrative jurisdiction. In practice, Chinese local governments primarily rely on command-and-control type approaches to regulate emissions, and the emission fees themselves only account for a small proportion of the regulatory burdens faced by polluters. Nevertheless, the fact that the local governments do have 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 Table VI, Panel B, 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

TABLE VI

POLITICAL ECONOMY OF WATER QUALITY MONITORING

	Polluting industries			Nonpolluting industries		
	(1)	(2)	(3)	(4)	(5)	(6)
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 versus 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 versus 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, and Titiunik (2014) for different kernel weighting methods are used for the estimation. Panel A examines how tax and waste discharge fees 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 $\leqslant$ 56 versus age $>$ 56). Panel C estimates the discontinuities separately for automatic and manual monitoring stations. * significant at 10%. ** significant at 5%. *** significant at 1%.

cannot be promoted to a higher level if their 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 they are 56 or younger in a given year, and "having weak political incentives" otherwise. We then assign a monitoring station either to an "incentivized" or "unincentivized" party secretary in a given year, based on whether the monitoring station is under the governance

of an "incentivized" leader at that time. The RD results show that when the prefectural city leader has strong political incentives, water quality monitoring has a large and statistically significant effect 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.[25]

Finally, we investigate how the manipulation of water quality readings by politicians affects environmental regulation enforcement. 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, whereas manual stations require technicians to conduct the tests manually.[26] Because it is difficult for local governments to manipulate data from the automatic stations, we expect a larger TFP gap around automatic stations.

Table VI, Panel C 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.

25. As an alternative way to check this result, we use the panel data set 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 Online Appendix Table S13.

26. 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. Please see Lin and Sun (2020) for more detailed discussions of the automatic water monitoring system.

VI.B. The 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 Table VII, Panel A, 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 effect on the TFP of 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 subsample null result should be interpreted with caution.

In Panel B, 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 policy makers mainly target large enterprises, and "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, 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 an attempt to address water scarcity in the north.[27] To do so, the central government imposed stringent requirements that the affected regions must ensure good water

27. 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.

TABLE VII

HETEROGENEOUS EFFECTS OF WATER QUALITY MONITORING

	Polluting industries			Nonpolluting 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, and 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%.

quality along the channeled river basins, which adds additional political stakes for the corresponding local governments. We thus split our sample into two subregions based on whether the location is designated as the water diversion project region. Our

results show that the effect 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.[28] 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 we use 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 we discuss the persistence of this aggregate abatement cost. Finally we evaluate the potential sources of bias in our calculation.

VII.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 log units, leading to a TFP loss of 0.36 log units (0.21 if we restrict to within-firm variation). Under several simple functional form assumptions and exploiting the sampling criteria of the ASIF and ESR data sets, we can link the two estimates and obtain the average pollution abatement cost for Chinese manufacturing firms.[29]

In Table VIII, Panel A, we report the estimated TFP loss

28. If TFP is reduced by x% in a year, the corresponding loss in industrial value-added can be calculated by $\frac{\text{VA}}{1-\text{x}\%} - \text{VA}$, where VA is the realized value-added in that year.

29. The technical details for linking the TFP and COD estimates are discussed in Online Appendix F.

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 5 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 Online Appendix F.

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, 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.[30] If we use the more conservative within-firm estimates (Table II), the estimated cost would still be around

30. 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

816 to 882 billion Chinese yuan, as reported in columns (4)–(6) in Panel B.

Although 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 industrial structures and regulatory enforcement practices are relatively stable over time. Table VIII, Panel C 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 (2016–2020). Applying our estimates to the production data and using 2015 as the reference year, we find that the five-year total loss in value-added would be 1,303–1,472 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 Panel C, columns (4)–(6).

VII.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. Because capital stocks depreciate by a low rate from year to year, the regulation-induced spikes in capital stocks would likely have long-lasting effects on firm productivity. This is confirmed by the dynamics of TFP during our sample period, as documented in Figure V: the upstream-downstream gap in TFP emerged after water regulation became stringent in 2003, and persisted throughout our sample period.

After 2007, the ASIF data set no longer collected information on firm value-added, so we are unable to track TFP dynamics in the longer run. However, because 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 2008–2012 ASIF data (the most recent data available to us) and estimate spatial discontinuity in capital stocks. As summarized in Online Appendix Table S14, we

extrapolating based on the pre-2003 trend in COD emissions. We discuss this alternative procedure in detail in Online Appendix F.

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's environmental regulation has become more stringent in recent years.

VII.C. Potential Sources of Bias

There are several reasons 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 data set. 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 nonpolluting industries is based on two- to three-digit industrial codes. This distinction does not rule out the possibility that some firms in the nonpolluting 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 nontrivial ways.

VIII. Conclusion

Like many other developing economies, China faces a stark trade-off between preserving basic environmental quality and sustaining robust economic growth. This article is the first to rigorously quantify the effects of environmental regulation on the country'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 compared with 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 (nonproductive) 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 effects of water quality monitoring on pollution. Using a firm-level emissions data set, we find that upstream polluting firms emit substantially less COD, NH_3-N, and industrial wastewater, as measured by 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 (2000–2007) led to a total loss in industrial output of more than 800 billion Chinese yuan.

This article 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 noncontractable 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 a political priority during our study period. Quantitatively, we document that (i) local government officials charge higher emissions fees for upstream firms while these firms actually emit less; (ii) local officials who stand a chance of being promoted to the provincial level have substantially stronger incentives to regulate upstream firms; and (iii) 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.[31] Second, our sample covers a relatively short period of time, whereas 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

31. 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.

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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SUPPLEMENTARY MATERIAL

An Online Appendix for this article is available at *The Quarterly Journal of Economics* online.

DATA AVAILABILITY

Data and code replicating tables and figures in this article can be found in He, Wang, and Zhang (2020), in the Harvard Dataverse, doi: 10.7910/DVN/LVS8VX.

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