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Indirect Value of Public Infrastructure Technology

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Abstract. Although prior research has primarily focused on the direct value of information technology (IT) and IT adoption by individuals and firms, this study explores the indirect value of IT in the form of public infrastructure technology. By exploiting a spatial discontinuity in water monitoring stations, we discover that firms located immediately upstream of water monitoring stations exhibit significantly lower levels of corruption than firms located immediately downstream. These findings are particularly noteworthy given that water monitoring stations have the potential to generate significant indirect value as they are not explicitly designed to mitigate corruption. Further analyses reveal that public infrastructure technology alone does not hold the key to mitigating corporate corruption. Instead, it is the synergistic interplay between public infrastructure technology and organizational change that drives the outcome. These findings contribute to a deeper understanding of the broader IT value landscape, emphasizing the indirect value of technological advancements in public infrastructure that were not originally intended for such benefit. Additionally, our findings highlight the benefits of leveraging existing infrastructure technology to address emerging societal needs.

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Keywords: corruption • public infrastructure technology • IT value • organizational change • technology complementarity

1. Introduction

In today's digitally interconnected world, the value of information technology (IT) has been extensively studied (Brynjolfsson 1996, Brynjolfsson and Hitt 1996, Melville et al. 2004, Brynjolfsson et al. 2021), with a particular emphasis on its *direct* effects on domains like consumer welfare (Brynjolfsson 1996, Mithas et al. 2016, Babar and Burtch 2020, Liu et al. 2022, Feng et al. 2024, Shen et al. 2024), business value (Bharadwaj et al. 2007, Nevo and Wade 2010, Grover and Kohli 2012, Havakhor et al. 2019), and innovation (Gómez et al. 2017, Trantopoulos et al. 2017, Guo et al. 2022). However, the *indirect* value of IT, particularly in the realm of promoting ethical business practices, remains an underexplored area of research. The term "indirect value of IT" is used to describe situations where IT artifacts have unintended consequences or unanticipated effects, despite not being designed for such purposes. An illustrative example is that the ride-hailing platforms, although not designed to impact the number of rape incidents, have been found to have a dampening effect on such occurrences (Park et al. 2021). Similarly, Liu et al. (2023) find that online food delivery platforms have an indirect effect to increase female labor market participation, despite lacking explicit intentions to do so. Moreover, existing literature on IT (direct and indirect) value primarily focuses on the adoption of IT artifacts by individuals (e.g., social media (Allcott et al. 2020), sharing platforms (Li et al. 2022), ride-hailing platforms (Burtch et al. 2018), crowdfunding platforms (Wang and Overby 2022)) or organizations (e.g., IT investment (Gómez et al. 2017), enterprise resource planning (Jia et al. 2020), supply chain management (Dong et al. 2009), healthcare IT (Ganju et al. 2022)). However, our research stands apart by examining the indirect value of IT in the context of public infrastructure technology and discussing its impact on corporate corruption.

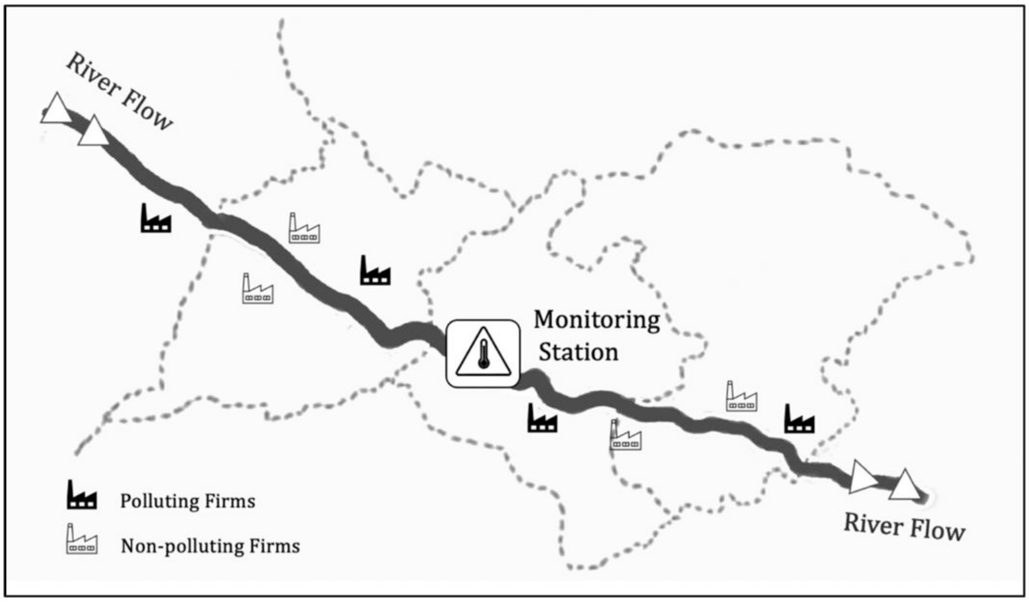
The issue of corporate corruption presents a major threat to stability and economic growth worldwide. According to the Dow Jones State of Anti-Corruption Survey conducted in 2014,[1] approximately one third of companies have reported losing business to their competitors who secured contracts through bribery. According to the estimation of Pei (2007), the direct expenses incurred because of corruption in China amount to approximately 3% of the country's annual gross domestic product (GDP). Corporate managers often corrupt to leverage their political connections to channel resources toward their firms or to evade regulations (Faccio 2006, Li et al. 2008). However, such actions can result in distortions that ultimately lead to suboptimal decision making and underperformance (Faccio 2006, Fan et al. 2007, Fisman and Wang 2015).

Recognizing the potential of public infrastructure technology as a catalyst for change, our study seeks to examine its indirect impact on reducing corporate corruption. We go beyond the traditional focus on individuals' or firms' IT adoption and delve into the broader context of public infrastructure technology, which encompasses technological advancements in public facilities. Specifically, the public infrastructure technology we examine is water monitoring stations. During the 1990s, the Chinese government constructed numerous state-controlled water quality monitoring stations, with the objective of gathering surface water quality information (e.g., the depth, speed, and width of surface water and water quality). This has provided a distinctive empirical context for identifying causality and assessing the impact of public infrastructure technology. As the water flows from upstream to downstream, the impact of technology (i.e., monitoring stations) on water quality is limited to upstream firms because downstream firms' pollution and emissions cannot be detected by the water quality monitoring stations (see Figure 1 for an illustration). In other words, companies situated in close proximity to water monitoring stations, either upstream or downstream, share many similarities, with the exception that upstream enterprises are subject to the influence of water monitoring stations. This allows us to utilize a regression discontinuity design to investigate the effects of public infrastructure technology.

Leveraging the spatial discontinuity in monitoring water pollution, we discover that polluting businesses located immediately upstream of water monitoring stations reduced corporate corruption spendings significantly compared with polluting firms located immediately downstream. The objective of the water monitoring stations was to assess the quality of water rather than to address issues of corruption. The results demonstrate that the employment of public infrastructure technology, particularly the water monitoring stations, yields an unintended impact on the corruptive activities of polluting enterprises.

Further analysis reveals, however, that the indirect impact of public infrastructure technology cannot be solely attributed to technological resources. We demonstrate that the complementarity of public infrastructure technology and organizational change is the key to mitigating corruption. In China, an organizational change has been implemented suddenly whereby water quality

Figure 1. Research Context



measurements obtained from water monitoring stations have been integrated as a fundamental metric for assessing the performance of the administrations in the regions where the companies are located. Moreover, our further investigation shows that the organizational change in isolation is not enough to produce the effect on reducing corporate corruption. Several other robustness checks confirm the validity of our regression discontinuity design and the findings.

By examining the relationship between public infrastructure technology, organizational change, and corruption, our research contributes to a nuanced understanding of the broader IT value landscape. The existing body of literature has traditionally concentrated on the direct effects of IT artifacts (Brynjolfsson 1996, Bharadwaj et al. 2007, Nevo and Wade 2010, Grover and Kohli 2012, Mithas et al. 2016, Gómez et al. 2017, Trantopoulos et al. 2017, Havakhor et al. 2019, Babar and Burtch 2020, Guo et al. 2022, Liu et al. 2022, Xu et al. 2024) and the indirect effects of IT adopted by individuals (Burtch et al. 2018, Allcott et al. 2020, Li et al. 2022, Wang and Overby 2022). Our study contributes to the field of IT value by drawing attention to the indirect effects of public infrastructure technology. Specifically, we highlight the unintended effect of such technology in the battle against corporate corruption during organizational change. By broadening our perspective on IT value and recognizing the complementary role of organizational change, we contribute to a deeper understanding of the strategies that can effectively promote ethical behavior and integrity.

Furthermore, our study holds implications for policymakers and practitioners involved in anticorruption efforts. Our findings demonstrate that the strategic reuse of existing public infrastructure technology to meet new emerging societal needs offers substantial advantages. By leveraging existing technologies like water quality monitoring, governments can extend benefits to wider populations, surpassing the original intended scope of the technology. Thus, the strategic use of technology, supported by organizational change, not only addresses immediate challenges but also secures long-term social welfare and environmental sustainability. This highlights the importance of an integrated approach that leverages technological advancements to fulfill governance objectives effectively and sustainably.

Next, Section 2 reviews related literature. In Section 3, we discuss the background of organizational change, water monitoring stations, and corruption in China. We then describe the data and present our empirical strategy in Section 4. In Section 5, we report our main results and discuss the underlying mechanisms. We then provide several robustness checks and additional analyses in Section 6. In Section 7, we conclude with a discussion.

2. Literature Review

2.1. Value of IT

Our study contributes to the literature on the value of IT. IT value research examines the benefits and strategic value of information technology (Hitt and Brynjolfsson 1996, Oh and Pinsonneault 2007). This topic has been extensively studied (Brynjolfsson 1996, Brynjolfsson and Hitt 1996, Melville et al. 2004), and researchers have adopted myriad approaches to assess the mechanisms through which IT value is generated and to estimate its magnitude (Mukhopadhyay et al. 1995, Kohli and Devaraj 2003, Li et al. 2023). The literature on IT value can be broadly classified into two categories: IT direct value, which examines whether the anticipated benefits of IT have been realized (Hitt and Brynjolfsson 1996), and IT indirect value, which investigates unintended consequences resulting from IT adoption. Our paper falls within the scope of the second category.

Existing research on IT value has predominantly focused on its direct value, examining how IT enhances productivity, fosters competitive advantages, and generates consumer value (Hitt and Brynjolfsson 1996). Regarding productivity, studies have found that IT spending leads to a positive increase in gross marginal product (Brynjolfsson and Hitt 1996) and contributes significantly to GDP growth (Dewan and Kraemer 2000), with varying impacts across industries (Mittal and Nault 2009). In terms of competitive advantages, IT significantly improves supply chain efficiency (Rai et al. 2006, Dong et al. 2009, Yao et al. 2019) and firm performance (Bharadwaj et al. 2007, Chakravarty et al. 2013, Tafti et al. 2013, Feng et al. 2019). It also helps mitigate diminishing returns to research and development (R&D) (Ravichandran et al. 2017), facilitates knowledge flows within alliances (Ravichandran and Giura 2019), improves quality and cost outcomes (Mishra et al. 2022), and promotes efficiency and innovation across multiple domains (Dellarocas et al. 2007, Nevo and Wade 2010, Gao and Hitt 2012, Gómez et al. 2017, Trantopoulos et al. 2017, Wang and Overby 2022). In terms of consumer welfare, studies have shown positive associations between IT investments and consumer surplus (Brynjolfsson 1996), as well as customer satisfaction (Mithas et al. 2016). Furthermore, in the transportation sector, IT has assisted commuters and local governments in managing urban traffic (Babar and Burtch 2020, Cheng et al. 2020, Rhee et al. 2022). In contrast to this body of literature, our study diverges by focusing on the indirect value of IT. Rather than examining the anticipated benefits of IT, our primary objective is to explore and analyze the unintended consequences that arise from its use.

The value of IT remains a relatively underexplored area of research, with only a limited number of studies addressing it, as shown in Table 1. For instance,

Table 1. Literature Review on the Indirect Value of IT

Paper	IT artifact	Areas	Key findings
Ozer et al. (2023)	LendingClub	Public Health	There is a strong and significant increase in the abortion rate following the entry of LendingClub.
Liu et al. (2023)	Online Food Delivery Platform	Labor Market	The entry of an online food delivery platform significantly increased the female employment rate.
Park et al. (2021)	Uber	Criminality	Uber's entry into a city is negatively associated with the number of rape incidents.
Allcott et al. (2020)	Facebook	Belief	Deactivating Facebook helps reduce political polarization.
Chan et al. (2019)	Craigslist	Criminality	Entry of Craigslist to a county lead to a 17.58% increase in prostitution cases.
Burtch et al. (2018)	Uber	Entrepreneurship	Uber platform entry has a negative and significant relationship with entrepreneurial activity.
Greenwood and Wattal (2017)	Uber	Criminality	The entry of Uber services led to a significant drop in the rate of homicides.
Chan et al. (2016)	Internet broadband	Criminality	Broadband availability increases racial hate crimes.
Greenwood and Agarwal (2016)	Craigslist	Public health	Internet enabled matching platform implementation led to a significant increase in HIV incidence.

research shows that the use of an Internet-enabled matching platform, which aims to facilitate social interactions and meetings among couples and groups, unintendedly leads to an increase in HIV incidence (Greenwood and Agarwal 2016) and prostitution cases (Chan et al. 2019). Similarly, Chan et al. (2016) discover an unexpected correlation between greater broadband availability, intended to provide high-speed Internet access, and a rise in racial hate crimes. The ride-hailing platform Uber, designed to facilitate the matching of passengers with drivers, unintentionally results in a reduction in homicide rates (Greenwood and Wattal 2017), a decrease in entrepreneurial activities (Burtch et al. 2018), and a decline in the occurrence of rape incidents (Park et al. 2021), despite not intending to bring about such outcomes. Moreover, Allcott et al. (2020) find that Facebook, a social media and social networking platform, unintentionally contributes to political polarization among individuals, although it was not designed to do so. Liu et al. (2023) find that online food delivery platforms, which act as intermediaries facilitating the delivery of food orders from restaurants to consumers, inadvertently contribute to the rise in female labor market participation. Ozer et al. (2023) discover that a peer-to-peer (P2P) lending platform, a microfinancing platform facilitating direct connections between borrowers and investors, is correlated with a rise in abortion rates among women, despite not being designed for such purpose. Our study adds to the limited yet growing body of literature on the unintended consequences of IT. Specifically, we demonstrate that water monitoring stations, originally established for scientific purposes, unintentionally help mitigate corporate misconduct, despite not being explicitly designed for such purposes. The significance of this field lies in the need for a comprehensive evaluation of the value and impact of IT by considering both the anticipated benefits and unintended consequences associated with its adoption.

Our research diverges from the current literature on the indirect value of IT in two distinct ways. First, the existing literature primarily addresses the adoption of IT artifacts by individuals (Table 1), such as social media (Zhu and Zhang 2010, Xu and Zhang 2013, Allcott et al. 2020, Kummer et al. 2020, Zhou et al. 2023), ride-hailing platforms (Greenwood and Wattal 2017, Burtch et al. 2018, Park et al. 2021), online matching platform (Greenwood and Agarwal 2016, Chan et al. 2019), food delivery platform (Liu et al. 2023), P2P lending platform (Ozer et al. 2023) and Internet broadband (Chan et al. 2016). However, none of the aforementioned studies explore the unintended consequences of public infrastructure technology. Even when considering the broader scope of literature that investigates both the direct and indirect value of IT, the prevailing emphasis remains on investigating IT adoption by individuals and organizations in areas such as crowdfunding platforms (Wang and Overby 2022), IT investment (Gómez et al. 2017), enterprise resource planning systems (Jia et al. 2020), supply chain management (Dong et al. 2009), and healthcare IT (Ganju et al. 2022). The academic literature has predominantly overlooked the influence of public infrastructure technology.

Second, although existing studies have identified the unexpected consequences of IT implementation in various domains (Table 1), including public health (Greenwood and Agarwal 2016, Ozer et al. 2023), labor market (Liu et al. 2023), criminality (Chan et al. 2016, Greenwood and Wattal 2017, Chan et al. 2019, Park et al. 2021), entrepreneurship (Burtch et al. 2018), and individual belief (Allcott et al. 2020), we expand the literature on indirect value of IT by focusing on ethical business practices. Such indirect value is noteworthy because the issue of corporate corruption presents a major threat to the stability and economic growth worldwide (Cheung et al. 2021, Griffin et al. 2022), leading to distortions that result in suboptimal decision making and underperformance (Faccio 2006, Fan et al. 2007, Fisman and Wang 2015).

2.2. Impact of IT on Corruption

Our paper closely connects to the literature about the impact of IT on corruption. Existing evidence of IT's influence on corruption is mixed. On the one hand, some researchers document that IT can be helpful in alleviating corruption because it improves information transparency (Srivastava et al. 2016, Sheryazdanova and Butterfield 2017, Sarker et al. 2021). On the other hand, studies on IT implementation in certain countries have shown that the intended goals of curbing corruption were not achieved (Davis 2004, Addo and Avgerou 2021).

Our study differs from this body of literature in two distinct ways. First, the IT implementations in previous studies are designed with the objective of anticorruption. However, in our paper, neither the public infrastructure technology nor the organizational change was specifically designed to address corruption. In other words, existing studies examine the direct effect of IT on corruption whereas our study investigate the indirect effect of IT on corruption. Second, our findings indicate that the mere enhancement of information transparency via technology may be insufficient in mitigating corruption. To mitigate corruption, it is essential to integrate technology with appropriate organizational change. These findings also extend beyond the explanation of Addo and Avgerou (2021) why IT sometimes failed in reducing corruption. They argue that the limited effects of IT on corruption is the result of constraints to organizational change exerted by relationships and institutions of patronage. Our paper highlights the importance of combining technology with complemented organizational change, thereby presenting a more holistic approach to mitigating corruption and improving overall institutional efficiency.

In summary, our research contributes to the literature by examining the indirect value of IT on ethical business practices in the context of public infrastructure technology, thereby extending the research on IT value and the effect of IT on corruption.

3. Background

3.1. Water Monitoring Stations

In the 1990s, the Chinese central government installed state-controlled water monitoring stations along major rivers, lakes, and reservoirs to scientifically examine hydrological features such as the depth, speed, and width of surface water. The water monitoring stations sample and analyze the water and then report the water quality information to China's National Environmental Monitoring Center (CNEMC). The water quality information includes the temperature (°C), pH, chemical oxygen demand (COD; mg/L), conductivity (μS/cm), turbidity (NTU), permanganate (mg/L), NH_3-N (mg/L), total phosphorous (mg/L), total nitrogen (mg/L), chlorophyII α (mg/L), (for lakes), and algal density (cells/L) (for lakes), as well as an overall assessment of the water. The overall assessment of the water is based on the environmental quality standards for surface water issued by the Ministry of Ecology and Environment.

The purpose of the water monitoring stations was to get a comprehensive understanding of the surface water quality in China. Guided by this motivation, the locations of the water monitoring stations were chosen to spatially monitor the neighboring water bodies. The stations cover all the major rivers, lakes, and reservoirs in China. According to the Ministry of Environment Protection, the factors that affect the location of the water monitoring stations include river flow, areas of the water surface, geographical features of the riverbed, and so on. In summary, the water monitoring stations are established and sponsored by the central government, and the locations were chosen in accordance with a whole host of scientific factors. In other words, nonscientific factors such as the needs of local officials, firms, and the local economy were excluded from the consideration when picking the location.

Because the locations of the monitoring stations were determined by scientific reasons, we can eliminate the concern that polluting firms lobbied the government to locate water monitoring stations far away from their locations to avoid being monitored. Furthermore, we conduct a robustness check to test whether the firms strategically relocated downstream to avoid pollution detection. The results in Table A7 in the Online Appendix dismiss this possibility.

Our study also avoids the concern that the local officials might manipulate data in their favor because we focus on state-controlled water quality monitoring stations. The technical specifications for automatic monitoring of surface water, issued by the Chinese Ministry of Ecology and Environment (MEE), specifies that state-controlled stations directly report water quality readings to the central government.[2] Therefore, local officials and firms do not have approaches to manipulate the readings.

These monitoring stations capture and measure emissions only within a few kilometers upstream, and they cannot detect the pollution from downstream firms and firms located far away. Therefore, only immediate upstream firms are influenced by the technology (i.e., water monitoring stations). This unique context provides us the opportunity to use regression discontinuity methods to study the impact of public infrastructure technology.

3.2. Organizational Change

In 2003, a significant organizational change in government was implemented whereby water quality measurements obtained from water monitoring stations were integrated as a fundamental metric for assessing the performance of the officials in the respective regions where the companies are located. In this section, we briefly introduce the organizational change.

Chinese President Hu Jintao formally proposed the "Scientific Outlook of Development" (SOD) in 2003, which is composed of solutions for maintaining sustainable development, enhancing social welfare, and combatting environmental problems. Following the SOD, MEP released detailed plans to reduce environmental pollution. Specifically, in 2003, the central government decentralized authority for monitoring surface and wastewater to local governments, and established a five-year plan for pollution abatement among all major rivers, including the Huai, Liao, and Hai Rivers.[3] In its 10th Five-Year Plan,[4] "by 2005, the readings of chemical oxygen demand (COD) and ammonia-nitrogen (NH_3-N) of water monitoring stations in Huai River should be lower than 64.3 ton/annual and 9.2 ton/annual, respectively. The readings of COD and NH_3-N in Hai River should be lower than 106.5 ton/annual and 20.5 ton/annual respectively. The readings of COD and NH_3-N in Liao River should be lower than 32.58 ton/annual and 5.2 ton/annual respectively. The readings of COD and NH_3-N in the water conveyance line of the 'South-to-North Water Diversion' project should be lower than 54.7 ton/annual and 7 ton/annual respectively. 87% of the quality readings of water monitoring stations along the 'South-to-North Water Diversion' project should reach Grade III by 2005 and the readings for the remaining water monitoring stations should not be worse than Grade IV. All state-controlled water monitoring stations should have water quality readings better than Grade V by 2005."

From then on, water quality readings, reported by the monitoring stations, turned out to be a factor of consideration for provincial leaders' political promotions after 2003.[5] Specifically, the official document explicitly stated that "the achievement of pollution abatement target become one component of cadre evaluation metric (KPI of the local officials)," which was the paramount political motivation to local officials.

Local government officials could enforce environmental regulations by interfering with the production process of polluting firms in various ways. Given the paramount political motivations to reduce emissions and to improve water quality, policies such as the Jiangsu Environmental Protection Enforcement Plan 2003 explicitly stated that local officials would be promoted only if the water monitoring stations reported good water quality.[6] As a result, this organizational change in government indeed reduced pollutant and emissions levels after 2003 (He et al. 2020).

3.3. Corruption in China

Corruption is an "economic and political evil" (Seligson 2002) in both developed and developing countries. It increases transaction costs, intensifies economic inequality, distorts resource allocation, undermines political trust, and fuels social unrest. Corruption has severely impacted nearly every Chinese sector, including law enforcement, military, medicine, education, and so on. In 1995, Transparency International ranked China as the 40th of 41 countries in the worldwide Corruption Perceptions Index.[7]

In China, firms might escape investigation, improve sales, leverage financial advantages, and avoid regulations by bribing officials for "protective umbrellas" (World Bank 1997). For example, in the coal mining industry, the central government delegated the management of state coal mines to local governments in 1998, which created opportunities for local officials to take bribes in exchange for overlooking mismanagement and regulation violations. As a result, the death rate of coal mine workers increased dramatically during the delegation periods (Jia and Nie 2017). The Zijinshan mining area bribed Chen Junan, director of the Shanghang County Environmental Protection Bureau, to protect the company from regular supervision, which led to a severe sewage leakage in 2010. This leakage polluted the Tingjiang River, killed fish in the river, and cost 22.2 million RMB (about US$3 million) in damages.

Some Chinese firms often conduct corruptive transactions and build relationships (*guanxi*) through banqueting, drinking, gift exchange, and so on. Specifically, businessmen usually build connections with government officials through "drinking at the banquet, singing in the karaoke clubs (KTVs), carousing in the nightclub, group visits to brothels and saunas, and playing mahjong in teahouses," and the bills are paid by the businessmen (Osburg 2018). Many business deals were thus sealed by the expensive dishes and fine liquors on the table and by paying and receiving bribes, kickbacks, and luxury gifts under the table. Such expenses are usually recorded as "entertainment and travel cost" (ETC), a standard expenditure item in the accounting book of Chinese firms. As the name suggests, ETC is used to cover entertainment (including banqueting, drinking, gift, karaoke, sports club membership, etc.) and travel expenditure (Cai et al. 2011). Therefore, ETC is often used as a proxy to measure corruption of businesses in the Chinese context (Cai et al. 2011, Zhu 2017, Agarwal et al. 2020, Cao et al. 2021, Griffin et al. 2022, Kim et al. 2023).

During our research sample period (1996–2009), the Chinese government did not lay a strong emphasis on anticorruption. Anticorruption became a priority only after 2012 when President Xi Jinping launched the largest organized anticorruption effort in Chinese history and successfully cracked down on corrupt officials. Among the measures, he banned alcoholic beverages at official banquets and required disclosure of government officials' personal assets. Thus, the corruption we observe in this study is not affected by anticorruption policies.

4. Research Design and Data

4.1. Research Design and Empirical Model

The main purpose of our empirical analysis is to identify whether public infrastructure technology has an indirect effect on corruption. Given that water monitoring stations can only measure and report the aggregate emissions coming from immediate upstream manufacturers, we use this spatial discontinuity in monitoring stations to apply a regression discontinuity framework to identify whether the public infrastructure technology could mitigate the corruption problem. The spatial distance is the running variable in which positive (negative) distance indicates that firms are located upstream (downstream) of their nearest water monitoring stations.

We use both nonparametric and parametric approaches to estimate regression discontinuity and find quite consistent results. Our main results are based on the nonparametric approach. This approach is widely applied in quasi-experimental research, and it provides point estimates and inference procedures that are more robust to parametric misspecification bias (Calonico et al. 2018).[8]

To illustrate the nonparametric estimation, let Y_i be the outcome variable of firm i (entertainment and travel costs as a proxy of corruption). Let c_i be the location relative to water monitoring: positive (negative) c_i indicates upstream (downstream). The treatment effect of water monitoring stations on corruption is

$$\hat{\beta} = \lim_{c \downarrow 0} E[Y_i | c_i] - \lim_{c \uparrow 0} E[Y_i | c_i]. \tag{1}$$

The intuition of the regression discontinuity is that the treatment is "as good as" randomly assigned in a neighborhood of water monitoring stations. Because whether the firms belong to the treatment or control group is "as good as" random, treatment and control firms are all else similar except that the treatment firms are being treated (i.e., being affected by the water monitoring stations). Hence, the average treatment effect is equal to the difference between the limits of the treated and control average observed outcome. We will show more details about the assumption in Section 4.3. In our case, as the distance between the firms and water monitoring stations approaches zero, the treatment effect is equal to the differences in corruption between upstream and downstream firms.

Following Hahn et al. (2001) and Imbens and Lemieux (2008), the conventional nonparametric estimation of $\hat{\beta}$ is

$$\min_{\beta,\, \gamma,\, \tau,\, \sigma} \sum_{i=1}^{N} K\left(\frac{c_i}{h}\right) [Y_i - \sigma - \gamma \times c_i - \beta D_i - \tau \times D_i \times c_i]^2, \tag{2}$$

where D_i is one if the firm is located upstream and zero otherwise, h is the bandwidth, and $K(\cdot)$ is the rectangle kernel function. As Hahn et al. (2001) and Imbens and Lemieux (2008) suggest, discontinuity is estimated using local polynomial regression, and γ, τ, σ are the parameters for the polynomial regression. Detailed derivations can be found in Imbens and Lemieux (2008). We calculate optimal bandwidth using the mean square error (MSE) optimal bandwidth method proposed by Calonico et al. (2014), because it has a smaller coverage error, and it is less sensitive to tuning parameter choices. We also use alternative optimal bandwidth selection methods to check the robustness and find consistent results as shown in the Online Appendix, Table A12. We implement triangular, Epanechnikov, and uniform kernel functions following Hahn et al. (2001). The kernel is used to weigh the observation around the water monitoring stations, which is commonly used in nonparametric estimation techniques. Uniform kernel means to compute the treatment effect using the unweighted observations. Triangular kernel and Epanechikov kernel put more weight on observations near the water monitoring stations than observations located far away from the water monitoring stations. The kernel density functions are different for the two kernels.

Conventional nonparametric regression discontinuity estimation is the most commonly used model. It requires a specified and balanced bandwidth, which is small enough to remove the smoothing bias yet large enough to ensure adequate precision. Its performance is quite sensitive to the bandwidth used; inappropriate bandwidths could bias the results. Thus, we also report the bias-corrected estimation proposed by Calonico et al. (2014), which removes the potentially large effect of unknown leading bias of the conventional estimator and justifies it by using the MSE-optimal bandwidth choices.

However, bias-corrected estimators have some unappealing properties such as potentially large-coverage distortions in applications and poor performance in finite samples. Therefore, we follow Calonico et al. (2014) and report the robust estimator. In addition to the benefit of correcting biases, this robust estimator offers excellent finite sample performance.

For each regression discontinuity model, we report estimators using conventional, bias-corrected, and robust methods with triangular, Epanechnikov, and uniform kernel types proposed by Cattaneo et al. (2020). This estimator is a nonparametric density estimator based on local polynomial techniques. The estimator is boundary adaptive and does not require prebinning of the data. The estimator is constructed by smoothing out the empirical distribution function using local polynomial techniques. Importantly, the estimator is an asymptotic distributional approximation with precise leading bias and variance characterizations, and a consistent standard error estimator. These properties apply to both interior and boundary points in a fully automatic and data-driven way. In other words, it does not require prior knowledge of the shape of the sample.

Our results are highly robust to different estimation methods and kernel types. In addition, we present comprehensive robustness checks in the Online Appendix, including alternative estimators, difference-in-differences analysis, alternative bandwidth selectors, alternative radius circles around the monitoring stations, and including covariates in the estimation. All the results from alternative specifications are highly consistent with our main findings. Furthermore, we conduct a placebo test by moving the water monitoring stations upstream or downstream by 2 km and then estimate using the same approach. As expected, we find that there is no difference in the corruptive behavior for firms located upstream and downstream relative to the fictitious stations, proving that our main findings are robust. All standard errors in our analysis are clustered at the water monitoring station level to eliminate concerns about the spatial correlation of the error term.

4.2. Data

4.2.1. Water Quality Monitoring Stations. We use the China Environmental Yearbook to collect information about water quality monitoring stations. They were constructed in the 1990s to measure water quality in major rivers, lakes, and reservoirs in China for scientific purposes. We exclude stations located on lakes and reservoirs because we could not identify the relative upstream and downstream locations between these stations and their nearest firms. This leaves 478 water monitoring stations to be geocoded.

4.2.2. Corruption. The ETC accounting category is commonly used to document both ordinary business expenses and costs for bribing government officials, clients, and suppliers in China (Cai et al. 2011, Huang and Li 2013). The association of ETC with firms' corrupt practices has been widely acknowledged in both news media and academic literature because of its frequent utilization by firms as a means of providing benefits to cultivate relationships with external entities (Huang and Li 2013, Zhu and Wu 2014, Cull et al. 2015, Lin et al. 2016, Huang et al. 2017, Kong et al. 2017, You and Nie 2017, Wei et al. 2020). Furthermore, Huang and Li (2013) pointed out that firms do not have incentives to lie about ETC in the survey because the ETC is normally below the maximum allowed amount set by China's taxation authorities. In addition, during our sample period, the accounting practice of ETC is not changed. Thus, we adhere to the existing body of scholarly works in utilizing ETC as a measure of corporate corruption.

Furthermore, we also demonstrate the connection between the accounting variables ETC and firms' actual misconduct in Table A1 in the Online Appendix. The Poisson regression analysis presented in Table A1 reveals a statistically significant positive correlation between the number of regulation breaches observed in firms and the variable ETC. This provides compelling evidence of the association between our measurement of ETC and firms' actual misbehaviors. However, because of the limited number of datapoints available, we were unable to utilize the data of firms' actual misconduct to perform regression discontinuity analyses in our sample periods.

We collect multiple officially released data sets to gather firm information, measure firm corruption, and conduct a thorough and robust analysis. The different sources can be cross-validated. Each data set has advantages and disadvantages. We will discuss them in greater detail.

The first data set we use is the Annual Survey of Industrial Firms (ASIF) 2004 data set, conducted by the Chinese National Bureau of Statistics (NBS). ASIF provides basic information (e.g., firm name, address, industry classification, ownership), and major accounting items (e.g., income, sales, and tax). Although ASIF surveys are conducted yearly, we only use ASIF 2004 because that was the only year that NBS surveyed and reported ETC. This cross-sectional data set covers all industrial firms with annual sales above 5 million RMB (about US$762,000) in China.

Although the ASIF data set contains some data irregularities, many empirical studies have used it for analysis. We clean the data following the practice of the previous literature (Brandt et al. 2012, Rudai 2015, He et al. 2020), which dropped about 1.71% of firms in the original data set.[9] First, we drop observations with missing key values, such as addresses and ETC figures. Second, we drop observations with negative values for variables that should be positive, such as employment and capital stock. Third, we drop observations that violate generally accepted accounting principles. For example, we drop the companies whose total assets were unequal to the sum of total liabilities and equity. Fourth, following He et al. (2020), we drop the firms that belong to parent multiunit firms, because subsidiaries may have reallocated production to avoid tighter regulations after 2003. Last, we winsorize the data by keeping records in which the values of our dependent variable (ETC) ranged from the 0.5th to 99.5th percentile.

We first draw a 10-km radius circle around each water monitoring station and keep only those towns within the circle. Then, combined with geolocation information about the water monitoring stations, we can determine whether each firm was situated upstream or downstream relative to its nearest station, and then calculate the distance. If a firm was upstream (downstream) to its nearest station, and downstream (upstream) to its second nearest station, we drop the observation to avoid ambiguity.

In addition, ASIF identifies industry categories of firms. Following the official Ministry of Environmental Protection (MEP) classification, we classify firms into two categories: polluting and nonpolluting. Nonpolluting firms could serve as a control group because neither technologies nor organizational changes aimed at reducing pollution would have had an impact on them.

The second data set we use is Chinese Private Enterprise Survey (CPES) 1996–2009, one of China's longest-lasting large-scale nationwide surveys providing key micro firm-level information. CPES is collected and supervised by the Privately Owned Enterprises Research Project Team. The team members are from the United Front Work Department of CPC Central Committee, All-China Federation of Industry and Commerce, State Administration for Market Regulation, and the Chinese Academy of Social Sciences. CPES has been used in hundreds of empirical studies in the last two decades (Jia 2014, Zhao and Lu 2016, Ge et al. 2019). CPES data are released as multiyear cross-sectional data sets, allowing an analysis of dynamic corruptive activities across years. Note that CPES provides multiyear cross-sectional data rather than panel data, because they surveyed different samples of private firms in different years.

Unfortunately, the address information for CPES firms is limited to zip code level only, so we can only roughly measure their relative distances from the nearest monitoring stations and upstream/downstream locations. Moreover, CPES is insufficient for classifying firms into polluting industries and nonpolluting industries.

The summary statistics of the data can be found in Tables A2 and A3 in the Online Appendix, which show the covariate balance and industry balance between upstream and downstream firms.

4.2.3. Geo-Data. The geocoding locations of ASIF firms are obtained through Baidu Map API (https://api.map.baidu.com/geocoding/v3/), which returns coordinates and outputs a confidence level parameter that measures errors of street addresses. We keep the coordinates with errors within 5 km (confidence level > 30).[10] We obtain geocoded information for each zip code from the National Bureau of Statistics and use the data to match with our firm data sets. We also obtain GIS data on the water basin systems from the Ministry of Water Resources.[11] We then use the ArcGIS software to identify firm-station upstream and downstream relationships and firms' distances to water monitoring stations. The summary statistics are presented in Table A4 in the Online Appendix. In addition, we collect the river length data of each administration in China from the National Geomatics Center of China.

4.3. Regression-Discontinuity Assumption Check

Our spatial discontinuity design basically assumes that firms located immediately upstream and downstream of water monitoring stations are similar. We thus check the manipulation of the assignment variable and examine the balances between firm-level characteristics of upstream and downstream firms (Lee and Lemieux 2010). If the assignment variable is correlated with the treatment, upstream and downstream firms would show significantly different characteristics. Table A2 in the Online Appendix shows the summary statistics and balance checks for variables including the firm's opening year, whether it is in a polluting industry, its profits, value-added tax, number of employees (men and women), capital stock, and intermediate input. Characteristics are all well balanced between upstream and downstream firms. Table A3 in the Online Appendix further demonstrates that firms in various industries are equally distributed on both sides of the monitoring stations.[12]

In addition, anticorruption became a priority only after 2012, which is after our sample periods. Therefore, there should be no sentiment change in corruption during our sample periods. To further check whether upstream and downstream firms have different sentiments toward pollution, we investigate whether upstream and downstream firms have different levels of investments in combating pollution. A *t*-test ($t = 0.836$, $p = 0.403$) suggests no difference.

5. Results and Mechanisms

5.1. Main Results

We report the nonparametric estimates using conventional, bias corrected, and robust estimation methods proposed by Calonico et al. (2014) with triangular, Epanechnikov, and uniform kernel types (Hahn et al. 2001) as discussed in Section 4.1. Each cell in Table 2 is a separate regression discontinuity estimate using one of the three estimation methods and one of the three kernel types. We use corruption and ETC interchangeably in the following sections.

Columns (1)–(3) of Table 2 report the regression discontinuity estimates of the ETC gap between the upstream and downstream private enterprises in the polluting industries in 2004. Columns (4)–(6) of Table 2 display results for private enterprises in the nonpolluting industries. In the polluting industries, firms located immediately upstream showed significantly lower ETC

Table 2. Private Enterprises: Upstream-Downstream Corruption Gaps (ASIF)

	Polluting industries			Nonpolluting industries		
Method	(1)	(2)	(3)	(4)	(5)	(6)
Conventional	−93.11**	−95.93**	−107.34**	−14.91	−15.27	−21.29
	(33.75)	(32.83)	(35.41)	(23.18)	(24.02)	(27.66)
Bias-corrected	−106.41**	−109.50***	−124.71***	−21.69	−23.79	−28.98
	(33.75)	(32.83)	(35.41)	(23.18)	(24.02)	(27.66)
Robust	−106.41**	−109.50**	−124.71**	−21.69	−23.79	−28.98
	(37.09)	(35.91)	(39.16)	(26.02)	(26.53)	(30.88)
Observations	3,502	3,502	3,502	9,288	9,288	9,288
Kernel	Triangular	Epanechnikov	Uniform	Triangular	Epanechnikov	Uniform
Bandwidth	11,100	10,970	7,834	11,729	11,650	9,384

Notes. Each cell represents a separate regression discontinuity regression. Data are from ASIF. The running variable is the distance between a firm and a monitoring station. A positive (negative) distance means the firm is located upstream (downstream). The negative coefficients indicate that upstream firms have lower ETC. The discontinuities at monitoring stations are estimated using methods proposed by Calonico et al. (2014) and the MSE optimal bandwidth proposed by Calonico et al. (2014) for different kernel weighting methods. Standard errors clustered at the monitoring station level are reported below the estimates.

*, **, and *** significant at 5%, 1%, and 0.1%, respectively.

than the downstream counterparts (90–125 thousand RMB or US$13,000–18,000 for each firm annually), as shown in Table 2, columns (1)–(3), which translates to 73.2%–101.6% reduction compared with the average corruption costs.[13] The regression discontinuity estimates are highly robust to different estimation methods and kernel types.

The results indicate that upstream firms in polluting industries engage in substantially less corruption than downstream firms, demonstrating the indirect effect of technology in public infrastructure on reducing corruption. Although the water monitoring stations are not designed for mitigating the incidence of corrupt practices of firms, our empirical analyses reveal that the deployment of this public infrastructure has unanticipated effects on reducing corporate corruption. For nonpolluting firms, the upstream-downstream corruption gap was much smaller and is not significantly different from zero (Table 2, columns (4)–(6)), suggesting that the indirect effect of the technology in public infrastructure is not universal across all firms. Given that the water quality readings of water monitoring stations are only influenced by the emissions of polluting firms, it is logical to infer that nonpolluting enterprises were not affected by water monitoring stations.

We visualize our findings in Figure 2, which plots corruption (ETC) against the distance between a firm and its nearest monitoring station. We also plot their 95% confidence intervals and overlaid the plot with a fitted curve to display the discontinuity around stations. Figure 2(a) shows a significant discontinuity in corruption levels among private enterprises in polluting industries around monitoring stations, with upstream firms exhibiting significantly lower corruption compared with their downstream counterparts. Figure 2(b) is the regression discontinuity plot for the corruption level of private enterprises in nonpolluting industries. Little corruption gap existed around monitoring locations for nonpolluting industries.

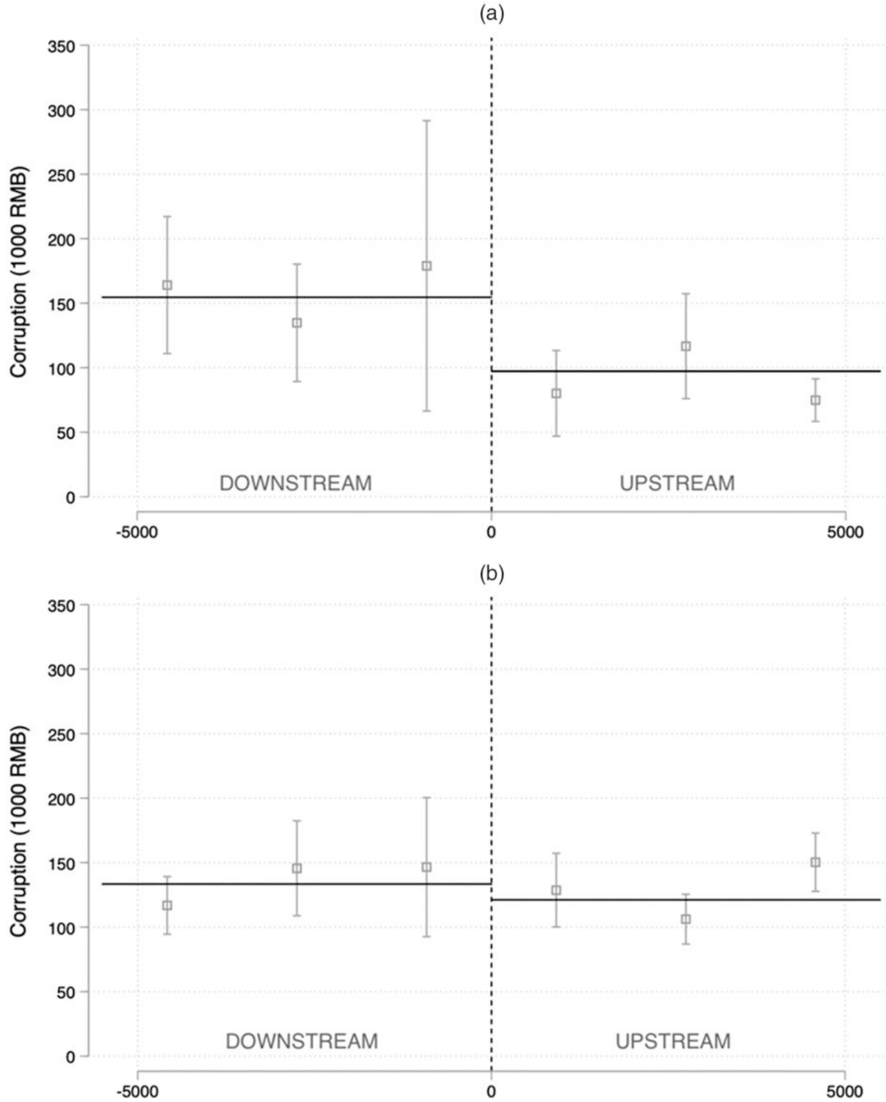
5.2. Mechanism

Having established that public infrastructure technology has a significant indirect effect on reducing corporate corruption, we explore the mechanisms driving this effect in this section. Specifically, we investigate the role of public infrastructure technology and its complementarity with organizational change in reducing corporate corruption. We also examine the role of organizational change in isolation.

Although previous studies have emphasized the value of technology alone, our analysis reveals that the technological resource alone does not hold the answer to the indirect effect of public infrastructure technology. Instead, our findings suggest that the indirect effect of public infrastructure technology in reducing corruption is contingent on whether it is complemented by organizational change in government. Furthermore, we find that the implementation of organizational change in isolation does not lead to the reduction of firms' corruption as well.

We first investigate whether technology alone can lead to the reduction of corruption. To investigate this, we compare the corruption gap between upstream firms and downstream firms before 2003 when there was no relevant organizational change at that time, which shows the effect of public infrastructure technology alone on corruption. The results are displayed in Table 3, columns (1)–(3). We find that most of the coefficients do not deviate from zero, indicating that the corruption from upstream firms of water monitoring stations was not different from the downstream firms. Therefore, we do not find supporting evidence showing that technology alone is effective in reducing corruption.

Figure 2. Regression Discontinuity Plot



Notes. (a) Polluting industries. (b) Nonpolluting industries.

Next, we examine whether public infrastructure technology, together with organizational change in government, has an effect on corruption. Subsequent to 2003, an organizational change was suddenly implemented whereby the water quality measurements obtained from water monitoring stations were incorporated as a fundamental metric for evaluating the performance of the administrations in the respective regions where the companies are situated, as discussed in Section 3.2. It should be noted that the organizational change was not implemented with the aim of addressing corporate corruption. Rather, the organizational change focused on environmental concerns. Results in Table 3, columns (4)–(6), demonstrate that the upstream firms significantly reduced their corruption costs (130,000–170,000 RMB or US$20,000–$27,000 for each firm annually) compared with their downstream counterparts after 2003, or 138%–180% lower relative to average corruption costs.[14] The regression discontinuity estimates are highly robust to different estimation methods and kernel types. The evidence indicates that the copresence of public infrastructure technology and organizational change can lead to the reduction of firms' corruption.

We further conduct an alternative difference-in-discontinuity estimation (Grembi et al. 2016), which takes the differences of the two upstream-downstream corruptive gaps before and after 2003 for polluting firms. The approach helps control effects around the cutoff point that are uncorrelated with the organizational change, such as changes in attitudes about corruptive behaviors. We report the difference-in-discontinuity estimates in

Table 3. Private Enterprises in Different Years: Upstream-Downstream Corruption Gaps (CPES)

	Before 2003			After 2003		
Method	(1)	(2)	(3)	(4)	(5)	(6)
Conventional	−1.95	−2.99	−4.51	−13.06***	−14.51***	−14.01***
	(2.76)	(2.66)	(3.46)	(2.78)	(3.04)	(3.04)
Bias-corrected	−1.90	−3.40	−6.53	−15.53***	−17.20***	−15.71***
	(2.76)	(2.66)	(3.46)	(2.78)	(3.04)	(3.04)
Robust	−1.90	−3.40	−6.53	−15.53***	−17.20***	−15.71***
	(3.59)	(3.80)	(4.62)	(3.66)	(4.02)	(5.14)
Observations	2,195	2,195	2,195	3,960	3,960	3,960
Kernel	Triangular	Epanechnikov	Uniform	Triangular	Epanechnikov	Uniform
Bandwidth	5.682	5.199	3.456	4.660	4.174	4.297

Notes. Each cell represents a separate regression discontinuity regression. Data are from CPES (1996–2009). The running variable is the distance between a firm and a monitoring station. A positive (negative) distance means the firm is located upstream (downstream). Negative coefficients indicate that upstream firms have lower ETC. Discontinuities at monitoring stations are estimated using methods proposed by Calonico et al. (2014) and the MSE optimal bandwidth proposed by Calonico et al. (2014) for different kernel weighting methods. Standard errors clustered at the monitoring station level are reported below the estimates. Year fixed effects are included in each regression.
*, **, and *** significant at 5%, 1%, and 0.1%, respectively.

Table 4. We find negative and statistically significant coefficients (100,000–200,000 RMB or US$15,000–30,000 for each firm annually) for upstream and downstream polluting firms before and after 2003. It shows that the complementarity between the public infrastructure technology and the organizational change is shown to play the strongest role in reducing corruption.

We then test whether our findings simply capture the effect of organizational change alone, rather than the indirect effect of the water monitoring stations or the complementary effect. In other words, we check whether misconduct behaviors would be reduced even in the absence of public infrastructure technology, so long as there is the organizational change. To determine whether our results are solely attributable to organizational change, we conduct a difference-in-differences analysis. Ideally, we need to choose provinces that had such organizational change implemented as the treatment group and some comparable provinces that did not have such organizational change as the control group. However, this organizational change was implemented nationwide simultaneously. Nevertheless, we notice that the intensity of the organizational change may vary across regions. We would then compare the difference in corruption between companies based in regions with more intense organizational change and those based in regions with less intense organizational change, both before and after the implementation of the organizational change. The estimates capture the effect of organizational change alone.

Table 4. Difference-in-Discontinuities Estimates of Upstream-Downstream Corruptive Gap Before and After 2003

Method	(1)	(2)	(3)
Conventional	−10.92*	−10.71*	−18.68*
	(5.03)	(4.91)	(7.87)
Bias-corrected	−13.22**	−13.00**	−21.72**
	(5.03)	(4.91)	(7.87)
Robust	−13.22*	−13.00*	−21.72**
	(6.41)	(6.02)	(8.41)
Observations	6,155	6,155	6,155
Kernel	Triangular	Epanechnikov	Uniform
Bandwidth	3.734	3.933	2.548

Notes. Each cell represents a separate difference-in-discontinuities estimate: the differences between corruption discontinuity before and after 2003. Data are from CPES. The running variable is the distance between the county center of a firm and a monitoring station. Positive (negative) distance means firms are located upstream (downstream). Discontinuities at monitoring stations are estimated using methods proposed by Calonico et al. (2014) and MSE optimal bandwidth proposed by Calonico et al. (2014) for different kernel weighting methods. Year-fixed effects are included in the estimation. Standard errors clustered at the monitoring station level are reported below the estimates.
*, **, and *** significant at 5%, 1%, and 0.1%, respectively.

We construct a measurement to indicate whether the firms belong to the treatment group (i.e., regions with more intense organizational change) or control group (i.e., regions with less intense organizational change). We develop a variable, *Long River*, which functions as a proxy for the likelihood that the organizational change will be implemented. Although the implementation of organizational change is executed at a national level, the intensity of the policy may differ across regions. As an illustration, the total length of all rivers within a given jurisdiction correlates positively with the degree of attention paid to issues of water pollution. In extreme cases, if a province lacks any rivers, it is possible that the issue of water pollution may not garner significant attention or concern. On the contrary, in provinces possessing a substantial number of rivers, greater emphasis will be placed on concerns pertaining to water pollution. Consequently, regions with longer rivers are more likely to implement stringent organizational changes regarding water pollution. Column (1) of Table 5 shows

Table 5. Effect of Organizational Change Alone on Corruption

	(1)	(2)
Long River × *After*	2.68	3.74
	(3.14)	(2.25)
Long River	−0.91	−0.79
	(2.25)	(2.11)
After	1.55	−1.07
	(2.96)	(1.14)
Log likelihood	−30,719	−3,004
Observations	6,155	595

Notes. The data are from CPES. The dependent variables are ETC. Long River is a dummy variable indicating whether the firms are located in places where the length of the river is above the median level. After is a dummy variable indicating whether the time is after 2003. The analysis in column (2) exclude firms located in administrations that have water monitoring stations.

*, **, and *** significant at 5%, 1%, and 0.1%, respectively.

the results where *Long River* is a dummy variable indicating whether the firms are located in places where the length of river is above the median level of river length. The interaction term *Long River* × *After* is not significantly different from zero. Therefore, we do not find supporting evidence that organizational change alone is sufficient to reduce firms' corruption.

To eliminate the concern that the length of the river may be correlated with the number of water monitoring stations, we restrict the sample in column (2) of Table 5 to firms located in regions without water monitoring stations. The interaction term *Long River* × *After* is not significantly different from zero. Hence, there is no evidence to substantiate the claim that organizational change alone is sufficient to reduce firms' corruption.

After demonstrating that the decrease in corruption is mainly driven by the combined effect of public infrastructure technology and organizational change, we proceed to delve more into the underlying mechanism that drive the results. We first demonstrate that firms do not voluntarily change their behavior on corruption, as evidenced by Table A5 in the Online Appendix. We find that there is no significant difference in entertainment and travel hours, which reflects the time/effort firm spent on corruptive activities between upstream and downstream private firms both before 2003 (columns (1)–(3)) and after 2003 (columns (4)–(6)). It indicates that the upstream and downstream firms spent nearly the same time and effort on corruption activities.

We then find that the reduction in corruption is driven by the different political promotion incentives of political officials. Recall that the organizational change linked water quality readings with political promotion of local officials. As a result, local officials tended to carefully consider the tradeoffs between accepting bribes and the potential negative impact of water readings on their political careers. By accepting bribes, they would gain positive utility from the money. However, as a tradeoff, the local officials must tolerate pollutants from polluting firms, and as a result, the water monitoring stations would report poor water quality readings to the central government, which would negatively impact their political prospects. Thus, the officials might be politically incentivized to reject a bribe from the upstream polluting firms, especially those leaders who strongly desire a political promotion.

To analyze this, we leverage the fact that, in China, the government imposes restrictions on individuals exceeding a certain age from being promoted (Kou and Tsai 2014), and the chance of being promoted decreases significantly at age 60 for prefecture leaders (Li and Zhou 2005). We therefore conduct regression discontinuity analysis by utilizing age 60 as the cutoff point.[15] The results in Table A6 in the Online Appendix supports our hypothesis. Firms in regions with politically motivated leaders (age below 60 years old) have lower corruption costs than those located in regions with nonpolitically motivated leaders (age above 60 years old). We observe significant negative coefficients only exist for upstream polluting firms (Panel A, columns (1)–(3)) but not for downstream firms (columns (4)–(6)) and nonpolluting industries (Panel B).

In summary, we discover that technological resources alone and the organizational change in government alone fail to explain the indirect effect of public infrastructure technology on corruption. Rather, the complementarity between public facility technology and organizational change has been demonstrated to play the role in reducing corruption. Furthermore, we demonstrate that firms do not voluntarily change their behavior on corruption, and it is the official leaders' political promotion incentives that drive the reduction.

6. Robustness Checks and Additional Analyses

In this section, we conduct additional robustness checks including (1) a manipulation check, (2) alternative estimation methods, (3) alternative radius circles, (4) alternative bandwidth estimation, (5) placebo tests, (6) inclusion of covariates, (7) heterogeneity analysis, and (8) alternative samples. More details can be found in the Online Appendix.

A potential concern about our main analysis is that polluting firms might avoid locating above monitoring stations, and instead, they moved downstream to escape regulations and fines. We test the distribution of polluting firms across monitoring stations (Table A7 in the Online Appendix) following the procedures proposed in Cattaneo et al. (2020). We find no discontinuity in the distribution of polluting firms across monitoring stations, which suggests that the possibilities of polluting firms relocating to downstream areas do not confound our main results.

We also conduct our analysis using alternative estimation methods including parametric estimates (Gelman and Imbens 2019) in Table A8 in the Online Appendix, difference-in-differences approach in Table A9 in the Online Appendix, and the Imbens and Wager (2019) estimator in Table A10 in the Online Appendix, and all the results are consistent with our main findings.

To remove the concerns that our results are sensitive to the choice of a 10-km cutoff, we conduct additional tests with cutoffs of 20 km (Panel A) and 30 km (Panel B) in Table A11 in the Online Appendix. The results are consistent.

The bandwidth chosen in our main result is a common MSE-optimal bandwidth selector (Calonico et al. 2014). To check whether our main findings are sensitive to optimal bandwidth selection methods, we use five alternative bandwidth selectors suggested by Calonico et al. (2018) and report the results in Table A12 in the Online Appendix, which are highly consistent with our main results.

We conduct placebo tests by using artificially relocating monitoring stations. We move the original stations upstream or downstream by 2 km (Table A13, Panel A), 3 km (Table A13, Panel B), and 4 km (Table A13, Panel C) and re-estimate the regression discontinuity models. The results show that the fake relative distance between firms and the placebo stations does not cause discontinuity of corruption at the fabricated cutoff. This test (Table A13 in the Online Appendix) confirms that the discontinuity of corruption exists only in actual monitoring stations, not placebo stations, thus providing additional evidence supporting our main findings.

In addition, we follow the suggestions of Lee and Lemieux (2010) to include additional covariates as a robustness check. As additional covariates, we include firm sales, firm value-added tax, the logarithm of the number of employees, the logarithm of one plus firm age, and the logarithm of province per capita GDP. Table A14 in the Online Appendix shows the results, which confirms our main finding.

Given the large variance among different provinces in China in terms of their local economy, leadership, corruption level, and water quality, we conduct the difference-in-discontinuities analysis to investigate the heterogeneity effect (Table A15 in the Online Appendix). We do not find evidence that corruption discontinuity between upstream and downstream polluting firms differs in terms of their social-economic condition (Panel A), regions' centralization level (Panel C), and water quality (Panel E). We observe that regions with politically motivated leaders experience larger corruption reduction gaps than regions with nonpolitically motivated leaders (Panel B). Moreover, high corruption regions show larger corruption reduction gaps than low corruption regions (Panel D). These findings offer additional corroborating evidence.

We further show the robustness of our results using alternative samples. We conduct our analysis using samples excluding the water monitoring stations located at the border of the provinces in Table A16 in the Online Appendix, samples including ambiguous firms that are located upstream of one water monitoring station and at the same time also located downstream of another water monitoring station in Table A17 in the Online Appendix, and samples including missing ETC in Table A18 in the Online Appendix. All the findings are consistent with our main results.

7. Conclusion

This study shed light on the indirect value of public infrastructure technology in reducing corporate corruption. Specifically, we present evidence of the unintended effect of technology on mitigating corruption during organizational change. Our findings suggest that technology itself does not drive the outcome, but it causes unintended consequences when combined with organizational change. By investigating the interplay between public infrastructure technology, organizational change, and corruption, we provide insights into the indirect value of IT and its impact on ethical business practices.

In the early 1990s and early 2000s, the Chinese central government set up hundreds of water monitoring stations for scientific purposes. We leverage the fact that water monitoring stations can detect, measure, and report pollution only for upstream polluting firms. Exploiting this spatial discontinuity, we implement a regression discontinuity design to compare the corruptive activities of upstream and downstream firms. We discover that upstream polluting firms have significantly less corruption costs than downstream polluting firms, although water monitoring stations were not explicitly designed for reducing corporate corruption. We conduct multiple robustness checks to confirm the validity of our regression discontinuity design and the results. These results highlight the unintended consequences of public infrastructure technology.

When analyzing the underlying mechanism, our empirical analysis shows that technology adoption alone is insufficient to reduce corporate corruption. Instead, we demonstrate that the effectiveness of public infrastructure technology in combating corporate corruption is contingent on the extent to which it is complemented by organizational change. Moreover, it is noteworthy that organizational change in isolation is inadequate to achieve such an impact as well. This highlights the need for a holistic approach that combines technological advancements in public infrastructure with organizational change. Furthermore, we find that firms do not voluntarily change their behavior on corruption, and it is the official leaders' political promotion incentives that drive the reduction.

Importantly, our study extends the literature on IT value, which has predominantly concentrated on the direct value of IT (Brynjolfsson 1996, Brynjolfsson and Hitt 1996, Melville et al. 2004). Instead, our research endeavors to shed light on the indirect effects of public infrastructure technology that have been adopted for specific purposes. Furthermore, our research moves beyond the traditional focus on individuals' IT adoption (Burtch et al. 2018, Allcott et al. 2020, Li et al. 2022, Wang and Overby 2022) or organizations' IT adoption (Dong et al. 2009, Gómez et al. 2017, Jia et al. 2020, Ganju et al. 2022) and explores the broader context of public infrastructure technology. In addition, our paper also distinguishes from the previous literature about the effect of IT on corruption (Davis 2004, Srivastava et al. 2016, Sheryazdanova and Butterfield 2017, Addo and Avgerou 2021, Sarker et al. 2021) by presenting the indirect influence of technology on corruption, highlighting the unintentional impact of technology. By doing so, we contribute to a more comprehensive understanding of the potential of IT to drive ethical behavior and integrity.

The implications of our study are significant for policymakers and practitioners involved in anticorruption efforts. By recognizing the indirect value of public infrastructure technology, policymakers can prioritize investments in technology-enabled public facilities and leverage their potential to create a conducive environment for ethical business practices. Additionally, practitioners can incorporate organizational change initiatives that align with and amplify the benefits of public infrastructure technology in reducing corruption. Furthermore, we show that governments can greatly enhance social welfare by utilizing pre-existing public infrastructure technology, such as water monitoring stations. Utilizing existing technology for social welfare demonstrates the potential to extend benefits to broader populations, surpassing the original intended scope of the technology.

Our work has some limitations. First, our finding may not be directly generalized to other countries with different political systems. However, the impact of public infrastructure technology on corporation corruption is substantial and meaningful in China, where the direct costs of corruption are estimated to amount to approximately three percent of the country's GDP annually (Pei 2007). The present study establishes and quantifies the indirect benefits of public infrastructure technology in mitigating corporate corruption. Such indirect effects of technology are often poorly measured (Brynjolfsson et al. 2019). Policymakers may find it necessary to consider these indirect effects when estimating the economic and societal effects of these technologies and making investment decisions. Second, we use ETC, an aggregate measurement of all corruptive activities, as our proxy for corruption but we are unable to establish different corruption categories. Third, our time window was relatively short. Firms may need time to adjust their production, investment, and corruptive activities. It would be interesting for future research to examine if there are long-term effects or if the reduced corruption can spill over to influence downstream firms.

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Endnotes

[1] See https://pro.wsj.com/press-room/dow-jones-risk-compliance-issues-sixth-annual-anti-corruption-survey/.

[2] See http://english.mee.gov.cn/Resources/standards/SpecificationsTestProcedures/201801/t20180126_430442.shtml.

[3] See http://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/200301/t20030101_66890.htm.

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

[5] In China, junior officials are appointed by higher-ranked government officials rather than chosen by voters.

[6] Original documents: http://www.js.gov.cn/xxgk/project/P0201606/P020160629/P020160629314508753226.pdf. More policy documents and translations can be found in He et al. (2020).

[7] See https://www.transparency.org/en/cpi/1995/results/. The Corruption Perceptions Index is based on expert and business executive rankings of countries. The composite index combines 13 surveys and assessments collected by various reputable institutions.

[8] We choose the Cattaneo et al. (2020) estimator by following several papers on spatial regression discontinuity that leverage this estimator (Campante and Yanagizawa-Drott 2018, Ehrlich and Seidel 2018, Ito and Zhang 2020). The running variable for Campante and Yanagizawa-Drott (2018) is the distance of the regions to the airport. The running variable for Ehrlich and Seidel (2018) is the distance of the city to the border. The running variable for Ito and Zhang (2020) is the distance between the city and the river.

[9] In the Online Appendix, Table A21, we alleviate the concern of sample selection by conducting *t*-tests about the characteristics for the sample before (column 2) and after (column 1) the data cleaning process.

[10] The confidence level ranges between 20 (error within 10 km) and 100 (error within 20 m). We also conduct robustness checks using samples with different confidence level cutoffs and find consistent results (Table A19 in the Online Appendix).

[11] See http://mwr.gov.cn/english/aboutmwr.html.

[12] Our results are quite robust when we remove the unbalanced industries (Table A20 in the Online Appendix).

[13] The average corruption costs for ASIF firms are 123,160 RMB.

[14] The average corruption costs for CPES firms are 94,900 RMB.

[15] Some leaders who are 58 or 59 (treatment group) might be similarly nonpolitically motivated as those who are above 60 (control

group). However, as long as some leaders under 60 are still politically motivated, this RD design should work fine. This situation is similar to the classical scenario where an RD design is used to examine the effect of class size. If all students performed equally well in both small and large classes, then we would not find any differences in their performance. However, as long as some students can perform better in small classes, the RD design would show a significant effect of class size on student performance. In our case, if all leaders who are below 60 are equally nonpolitically motivated as those above 60, then we should not identify any differences in the outcome variable. Given the fact that we find a significant difference in the outcome variable, we conclude that the discontinuity at age 60 serves well as an identification device.

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