Benefits and costs of campaign-style environmental implementation: evidence from China’s central environmental protection inspection system

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Abstract
Campaign-style environmental implementation (CEI) is widely exerted in environmental protection, while its benefits and costs are controversial. We take advantage of the Central Environmental Protection Inspection (CEPI) System—a latest and distinguished form of CEI launched by China in 2016, as a quasi-natural experiment, to compare the benefits and costs of CEI based on water pollution effect estimates. Our results based on the annual panel data from 500 cities during 2009–2018 show that CEPI significantly reduced water pollution by an average of 20.7%. Further cost–benefit analysis based on the estimates of water pollution reduction shows that the potential health benefits of mortality and morbidity reduction resulting from CEPI are at least $12.26 billion, without bearing additional economic costs. We also explore why CEPI is cost-effective and find that CEPI reduces water pollution and becomes cost-effective mainly through deterring local officials, punishing polluting enterprises, and increasing public participation in environmental governance.

Keywords Campaign-style environmental implementation · Cost–benefit analysis · Central Environmental Protection Inspection · Water pollution · Difference-in-differences method

Introduction
Campaign-style environmental implementation (CEI), a particular type of policy enforcement incorporating high concentrated mobilization of governmental resources under political sponsorship to realize a specific pollution reduction goal in a limited time (Liu et al. 2015), has emerged as one of the most widespread and long-lasting strategies of environmental protection in China (van der Kamp 2017). CEI’s measures are abrupt and severe, such as forcibly closing down entire polluting industries, arbitrarily demolishing outdated factory equipment, and levying high fines to polluting enterprises. Through these measures, CEI may be effective in improving environmental quality, but it is also an extremely costly strategy (Jia and Chen 2019). Whether it is necessary to conduct such high-cost CEI is still controversial. However, little systematic knowledge is known about CEI’s benefits and costs, despite the enormous policy implications. In this study, by estimating CEI’s impacts on water pollution, we conduct a calculation to compare the benefits and costs of CEI based on water pollution effect estimates.

More specifically, we take advantage of the Central Environmental Protection Inspection (CEPI) System promulgated by China in 2016 as a quasi-natural experiment and employ a difference-in-differences (DID) method to empirically quantify the potential health benefits and economic costs of CEI. And we also explore the mechanism through which the benefits and costs happen. We find that the potential health benefits of CEPI from reduced mortality and morbidity due to improved water quality are at least $12.26 billion, while CEPI does not cause a significant loss to the Chinese economy. The actual return from CEPI would be even greater, considering that we have only calculated the health benefits from the partial reduction in disease caused by water pollution and that CEPI has mainly eliminated the outdated production capacity.
CEPI, a latest and distinguished form of CEI launched by China in 2016, provides us a perfect setting for investigating the benefits and costs of CEI. CEPI is a watershed moment in the history of China’s environmental inspection (Li et al. 2020). Under CEPI, the central government sends inspection teams led by ministry-level cadres into various provinces to check whether local governments implement environmental protection policies and some prominent environmental issues. It then requires local governments to fulfill their enforcement responsibilities (Xu et al. 2020). Every province will receive a CEPI feedback list after completing the inspection, covering all major environmental problems in the water, air, soil, and other environmental issues. The provincial governments must provide corrective action plans based on the lists to address these major environmental pollution problems. We take advantage of CEPI as a quasi-natural experiment to estimate the benefits and costs of CEI.

We make four main contributions to the literature. First, to our knowledge, this paper is the first one to focus on the benefits and costs of CEI in the world’s biggest developing country. Existing research has focused chiefly on how CEI affects pollution reduction (He and Geng 2020; Jia and Chen 2019; Wu and Hu 2019), firm performance (Tian et al. 2019; Zeng et al. 2021), and social involvement (Li et al. 2020; Xiang and van Gevelt 2020). The lack of scientific evidence on the health benefits and economic costs of CEI makes its effectiveness controversial and thus hinders the government to better launch CEI. Our empirical results highlight the enormous health benefits from reduced mortality and morbidity resulting from water pollution reduction of CEI in the world’s biggest developing economy, many of which are suffering the worst health burden from severe pollution (Landrigan et al. 2018). CEI’s success in China provides a benchmark for cost–benefit policy discussions on launching CEI in other countries.

Second, we add to an emerging strand of literature estimating the impact of environmental implementation on water pollution. Due to data availability and quality, existing studies mainly focus on the effects of environmental implementation on air pollution, while water pollution has largely been ignored (Gray 2015). Water pollution has profound adverse impacts not only on human health but also on ecosystem services (Greenstone et al. 2021). While the air quality in China has upgraded in the past decade, the water quality, especially the groundwater quality, has degraded: almost 67% of groundwater does not meet drinking water standards, 190 million people got sick, and 60,000 people have died from diseases because of contaminated water every year in China (World Bank 2007). Thus, understanding CEI’s effect on water pollution is crucial for the government to control water pollution better.

Third, we test the mechanism underlying the benefits and costs of CEI. Previous studies mostly lack the test of the mechanism of CEI. One exception is Jia and Chen (2019), who propose three mechanisms of CEI—shuffle the local incentive structure, alter the internal bureaucratic dynamics, and ignite public participation. However, they only offer theoretical explanations and exploratory evidence, but not empirical analysis for these three mechanisms. Our paper complements the study of Jia and Chen (2019) by empirically analyzing the mechanisms involved in CEI and thus can help the government find out which type of policy tools could be used to strengthen CEI’s performance.

Fourth, our paper also relates to the growing discussion on the political economy of environmental regulation by conducting a cost–benefit analysis and showing CEI’s working mechanisms. CEI’s effectiveness is always controversial, and many scholars have doubted why the Chinese government chooses CEI—an unsophisticated, costly method, as the primary means for pollution control (Liu et al. 2015; van der Kamp 2017). Our findings highlight that if health benefits are considered, the advantages of CEI are more pronounced, and thus CEI may be a more reasonable choice for an authoritarian state, such as China. Moreover, as the largest developing country in an authoritarian system, our analysis in China is globally relevant that can provide an intermediate to figure out the effectiveness and working mechanisms of CEI, which is beneficial to other developing or transitioning countries.

The remainder of this paper is structured as follows. The “Literature review” section provides a review of the relevant literature. The “Background” section introduces the policy background of CEPI and its impact on pollution control in China. The “Data and method” section provides an overview of the data and methods needed for this paper. The “The effects of CEPI on water pollution control” section reports the baseline results of the impact of CEPI on water pollution. The “Benefits and costs of CEPI” section shows the estimation results of the benefits and costs of CEPI based on the water pollution effects estimation. The “Mechanisms: Why CEI is cost-effective?” section explores the mechanisms why CEPI is cost-effective. The “Conclusion” section presents conclusions and corresponding policy recommendations.

**Literature review**

CEI can enable the enforcement of priorities set by the central government at the local level, thus achieving environmental goals in a short period of time (van Rooij et al. 2017). As a result, CEI is increasingly favored by those in power and become an important tool for solving environmental problems (Kostka and Zhang 2018).

With a high concentration of resources and political support, CEI is widely believed to be effective in improving environmental
quality (Xu et al. 2020; Zhao et al. 2020; Wang et al. 2021a, 2021b). However, there is a heated discussion about the short- and long-term performance of CEI in the environmental field (Jia and Chen 2019). Some scholars stated that CEI can only reduce pollution in the short term. van Rooij (2006) pointed out that some of the polluting companies that were shut down for violations resumed production just weeks after CEI ended, so CEI’s effects are not sustainable. Kostka and Zhang (2018) contended that although CEI can achieve immediate results, the long-term performance of CEI is difficult to achieve owing to the lack of accountability mechanisms and insufficient public participation. Wu and Hu (2019) also found that the positive effect of CEI on air quality is unsustainable. While other scholars argued that CEI is long-term effective in improving environmental quality. Liu et al. (2015) contended that CEI can obtain long-term environmental performance through resource mobilization and redistribution of rights to achieve more stringent regulation. Jia and Chen (2019) found that the policy effect of CEI does not disappear after the campaign ends but rises and persists. Quan (2020) and Li et al. (2020) argued that CEI can have a long-term effect by improving the government’s enforcement capacity and public participation.

The main reason for this conflicting view is that previous studies have often lacked measurement of the costs and benefits of CEI. It is an indisputable fact that CEI may bring some other negative effects while improving the environment. For example, in the “eliminate backward production capacity” and “close small factories” actions in 2010 and the “Air Pollution Prevention and Control Action Plan” in 2013, the government used very drastic enforcement measures to achieve policy goals, such as immediately shut down polluting enterprises and cutting off water and electricity of factories, to force the enterprises to stop production (Kostka and Hobbs 2012; Kostka and Zhang 2018). This approach will not only disrupt the fairness of the enforcement process and hinder the establishment of regular enforcement mechanisms (Ma 2017; van Rooij et al. 2017), but will also inhibit local development and employment, resulting in significant economic costs (van der Kamp 2017).

This paper tries to complement the prior studies by taking CEPI as one type of CEI and conduct an empirical examination to identify the costs and benefits of CEI. Also, this paper attempts to reveal the transmission mechanism of CEI on pollution control and thus can help us to understand the specific working mechanism of CEI.

**Background**

**CEPI in China**

One major critical challenge in environmental management in China, as well as many other developing countries, is the deficit in policy implementation (Shimshack 2014; Duflo et al. 2018; Li et al. 2019). In the Chinese “top-down” environmental regulation structure, the effectiveness of environmental regulations depends mainly on the implementation efforts of local governments (Tian et al. 2019; Sun et al. 2021). However, although the willingness of the central government to govern the environment is strong, the local officials are more inclined to sacrifice environmental quality in exchange for economic development owing to the drive for promotion (Pang et al. 2019). Therefore, there is a conflict of interest between the central government—the policymaker and the local governments—and the policy implementers, in environmental governance targets (Li et al. 2016), which leads to a growing phenomenon of weak implementation and lax regulation by local governments in environmental management (Ran 2013; Yu and Wang 2013).

Against this background, CEPI, as the latest and distinguished form of CEI, has been officially launched in January 2016 to improve the implementation effectiveness of environmental management (Li et al. 2020). Different from previous environmental regulation means that simply supervise enterprises, CEPI focuses on supervising governments to impose pressure on local governments and to force them to fulfill their environmental implementation responsibilities (Ding et al. 2021; Xu et al. 2020).

CEPI consisted of five successive batches, starting in January 2016 and ending in September 2017, and covered all 31 provinces in China. Figure 1 reports the location distribution of the provinces inspected in each batch. We can find that geographically each batch covers provinces in the Chinese three East-Central-West regions, indicating there is no geographical bias in the sample selection process, and there would be no difference in CEPI implementation.

CEPI has resulted in unprecedented investigations and punishments. Data show that by the end of 2017, the inspection team had received more than 100,000 letters of complaint from the public. A total of 17,873 governmental officials and cadres were interviewed, 17,402 were held accountable, and 1,484 violators were detained. These investigations have resulted in unprecedented punishments with over 1.33 billion RMB (U.S. $203 million) worth of fines being levied on violated companies. The specific data of investigations and punishments for each batch are shown in Table 1.

**CEPI and pollution control**

With extraordinary resource mobilization and high concentrated political inputs, CEPI is generally regarded as an effective measure to reduce pollution (Kostka and Zhang 2018). This can be explained through the four procedures of CEPI.
The first procedure is stationing. During the stationing, the CEPI team conducted an approximately unannounced month-long environmental protection inspection of local party committees and governments and related departments through listening to reports, access to information, and field visits and reports from the public. In areas with ineffective environmental protection, severe ecological damage, prominent environmental problems, or deteriorated environmental quality, measures such as correspondence, interviews, accountability, restrictions on approvals, and notifications are taken and publicly exposed.

The second procedure is report feedback. The CEPI team will access the whole performance of the inspected cities and report a comprehensive inspection result to the central government. The report describes aspects needing rectification, such as lack of environmental regulations or inadequate pollution control. And after consideration, the local provincial governments will receive a list of CEPI feedback comments.

The third procedure is rectification and enforcement. Local provincial governments must issue a plan for collating the CEPI feedback within 1 month and making it public.
The rectification plan should respond in detail to everything mentioned in the CEPI report. Meanwhile, the CEPI team will also check the rectification enforcement to prohibit superficial, selective, and emblematic rectification.

In addition, CEPI has moved from one-time enforcement to a routinized one that may have long-term effects on pollution reduction (Jia and Chen 2019). The “Regulations on the Work of CEPI” issued in 2019 has clearly stated that CEPI will be carried out every 5 years, indicating a tendency of normalization and institutionalization. This particular tendency of CEPI may change local governments’ behavior, public opinion, and enterprises’ responses (Karplus and Wu 2019). For instance, enterprises are more likely to take powerful measures to reduce pollution due to the threat of long-term sanctions, and local governments may focus more on pollution reduction.

Data and method

Data

To evaluate the effect of CEPI on water pollution control, we collect water pollution data, CEPI data, and some factors that influence CEPI’s implementation. We selected annual panel data of 500 cities (including prefecture-level and county-level cities) from 2009 to 2018 as our study sample.

Water pollution data

As we stated above, we conduct the cost–benefit analysis based on investigating the impact of CEI on water pollution. Following the previous literature of He and Perloff (2016) and Pan et al. (2020), we select the per capita urban untreated sewage discharge (PUUSD) to represent water pollution. The reason is that untreated wastewater discharge is a major contributor to water pollution in China (Hu and Cheng 2013). Water quality tends to deteriorate severely when the rivers flow through urban areas owing to a large amount of wastewater they receive (World Bank 2006). PUUSD is measured as the per capita urban wastewater discharge amount minus the per capita urban wastewater treatment amount. To eliminate heteroscedasticity, PUUSD is transformed into a natural logarithmic form.

CEPI data

We choose cities having water pollution problems in CEPI reports in the first and second batches that occurred in 2016 as our treatment group and the remaining cities as the control group. The reason for this is that the CEPI reports cover a range of ecological and environmental problems in the water, air, and soil, occurring in local cities and implement these problems to local governments. Local governments tend to rectify these problems mentioned in the CEPI reports in their jurisdictions to respond to the inspection. However, as we stated in our introduction section, we focus on water pollution problems, so the cities with water pollution problems are used as the treatment group in this paper.

In addition, the samples in the trial round—Hebei province—are excluded from our analysis to avoid potential bias since Hebei province is a pilot province with more severe pollution (Jia and Chen 2019). We also eliminate the cities having water pollution problems in the third and fourth batches for two reasons. One is that these two batches started in 2017, which is a really short time to analyze their effect on pollution reduction. Another is that the central government also launched the CEPI “retrospective” in 2018, selecting 20 provinces across the country for further inspections to test the implementation of local governments’ rectification (Li et al. 2020), which will make it harder to estimate the net effects of the third and fourth batches. In total, we select 500 cities as our study sample.

Specifically, we manually downloaded the CEPI reports in all provinces and searched the cities with water pollution problems. There are 57 and 47 cities with water pollution problems in the first and second batches, respectively. Therefore, we choose these 104 cities with water pollution problems as our treatment group and the remaining 396 cities with non-water pollution problems as the control group.

Control variables

The premise assumption of causal identification using the DID approach is that the CEPI cities and the non-CEPI cities share common temporal trends in the absence of CEPI implementation. However, since the selection of cities with water pollution problems was non-random, which would pose a potential threat to the previous assumption. Therefore, it is possible that the discrepancy in PUUSD between the CEPI and non-CEPI cities after the CEPI implementation could be owing to their pre-existing differences.
Table 2 Descriptive statistical analysis of variables

| Variable                  | Definition                                                                 | Mean      | S.D       | N  |
|---------------------------|---------------------------------------------------------------------------|-----------|-----------|----|
| PUUSD                     | Per capita urban untreated sewage discharge (log)                          | 1.227     | 1.293     | 4,759 |
| Industrial structure      | The ratio of the added value of secondary industry to GDP                  | 0.478     | 0.136     | 4,979 |
| Population density        | The ratio of the total urban population to the urban district area         | 609.329   | 722.953   | 4,994 |
| Provincial capital-adjacent city | = 1 if a city is provincial capital-adjacent city; = 0 otherwise       | 0.284     | 0.451     | 4,999 |
| City’s administrative level | = 1 if a city is prefecture-level city; = 0 is county-level city      | 0.404     | 0.491     | 4,999 |

To overcome this difficulty and enhance the accuracy of identification, we select some control variables by referring to the method of Gentzkow (2006). Specifically, we first find the key factors that influence the division of the CEPI and non-CEPI cities and then control them. According to the “Central Ecological Environmental Protection Inspections Work Regulations” issued by the central government, it is specified that areas with major environmental problems and severe deterioration in environmental quality would be the focus of CEPI. According to this criterion, we selected the following four variables as our control variables.

1. Industrial structure. This variable is measured by the ratio of the added value of secondary industry to GDP. Cities with a higher percentage of secondary industry added value over GDP are more likely to be selected as CEPI cities. In general, the secondary industry is the main contributor to environmental pollution (Yang et al. 2019). The higher the ratio of secondary industry added value over GDP in a city, the more serious the environmental pollution problem may be in that city.

2. Population density. This variable is measured as the ratio between the number of people in the urban area and the urban area’s size. Cities with a greater population density are more likely to select as CEPI cities because population density is a primary contributor to environmental pollution (Dinda 2004).

3. Provincial capital-adjacent city. This is a dummy variable indicating whether the city is the capital city of a province or its adjacent. Non-provincial capital-adjacent cities may be more likely to be CEPI cities than provincial capital-adjacent cities. This is because non-capital-adjacent cities are farther away from provincial governments so that the local provincial governments may have weaker environmental regulation, and thus non-capital-adjacent cities are also more likely to incur environmental problems (Wang and Chen 2020).

4. City’s administrative level. This is a dummy variable indicating whether a city is a prefecture-level city. Prefecture-level cities are also more likely to become CEPI cities than county-level cities. This is because prefecture-level cities have a larger administrative area, a larger population, a higher degree of industrialization, and face an increased political pressure (Sun et al. 2021). They may be more susceptible to environmental problems and be subject to inspection (Li and Xu 2020).

The data of the above variables are from China City Statistical Yearbook and China Urban Construction Statistical Yearbook. Due to the missing values in some years of some county-level cities, this paper supplements them by looking into Statistical Yearbooks at the province and city levels. Finally, we get the panel data of 500 cities in China from 2009 to 2018. Table 2 shows the descriptive statistics of the above variables.

Empirical strategy

To prevent some endogenous problems, such as omitted variables and measurement errors from interfering with the study results, this paper regards CEPI as a quasi-natural experiment and examines the impact of CEPI on water pollution using a DID method.

First, we construct our baseline regression model with reference to the setting of Li et al. (2016) to estimate the average effect of CEPI on water pollution. Compared to the general DID model, this model is improved in two ways: (1) we use an interaction term between the policy dummy variable and time to control for the differences in time trends between CEPI cities and non-CEPI cities; (2) we assume that the effect of control variables on water pollution follows a unique time trend and use an interaction term between the control variables and a time polynomial to control for the differences in the temporal evolution of water pollution correlated with CEPI. The baseline regression model takes the following form:

\[ PUUSD_{it} = \alpha_0 + \alpha_1 CEPI_{it} + \gamma Treatment_{it} \times T + (Control_{it} \times f(T)) \left( \theta + \mu_i + \lambda_t + \epsilon_{it} \right) \]

where \( PUUSD_{it} \) represents the per capita amount of urban wastewater discharge. \( CEPI_{it} \) is the CEPI variable that

\[ \text{http://www.gov.cn/xinwen/2019-06/17/content_5401085.htm} \]
equals 1 in the years after city $i$ implemented CEPI and 0 otherwise. Specifically, $CEPI_{it} = \text{Treatment}_i \times \text{Post}_t$, where $\text{Treatment}_i$ equals 1 if city $i$ belongs to CEPI cities and 0 otherwise; $\text{Post}_t$ equals 1 if year $t$ is after 2016 and 0 otherwise. $\text{Treatment}_i \times T$ represents the linear time trend of treatment, of which $T = \text{year} - 2008$. $\text{Control}_{it}$ denotes a sequence of control variables listed in Table 2; $f(T) = T + T^2 + T^3$ is a 3rd-degree polynomial of $T$. $\text{Control}_{it} \times f(T)$ controls the time evolution trend of the control variables on water pollution. In addition, this model is a two-way fixed effect model, in which $\mu_i$ and $\lambda_t$ represent the city fixed effect and the time fixed effect, respectively. $\epsilon_{it}$ is the random perturbation term. $\alpha_i$ is the core estimation parameter of this paper, which represents the net benefit of CEPI on water pollution control. If $\alpha_i < 0$, it means that CEPI does contribute to water quality improvement, and the policy is effective.

Furthermore, this paper uses the event study method proposed by Jacobson et al. (1993) to study the dynamic effects of CEPI on water pollution, which also can test the common trend before the event shock. The specific estimation model is as follows:

$$PUUSD_{it} = \beta_0 + \sum_{k=-7}^{2} \beta_k \text{After}_{it}^k + \gamma \text{Treatment}_{it} \times T + (\text{Control}_{it} \times f(T)) \theta + \mu_i + \lambda_t + \epsilon_{it}$$

(2)

where the dummy variable $\text{After}_{it}^k$ equals 1 if $t - 2016 = k$ and city $i$ belongs to the CEPI cities, 0 otherwise; $k = -7, -6, -5, -4, -3, -2, 0, 1, 2$. And we treat the first year before CEPI implementation as the base period.

The effects of CEPI on water pollution control

The average effects of CEPI on water pollution control

Columns (1) and (2) in Table 3 show the average effect of CEPI on water pollution control. In column (1), we only controlled the city and year fixed effects. The estimated coefficient of the core explanatory variable CEPI is $-0.234$ and is significant at the 1% significance level. It indicates a significant negative causal relationship between CEPI and wastewater discharge. That is, CEPI can significantly reduce PUUSD. As shown in column (2), the coefficient of the core explanatory variable CEPI remains
significant after we further included the treatment time trend and the control variables. Specifically, CEPI can contribute to a 20.7% reduction in PUUSD for the CEPI cities than the non-CEPI cities. Therefore, we draw a preliminary conclusion that CEPI significantly reduces water pollution.

**The dynamic effects of CEPI on water pollution**

In the previous sub-section, we only analyze the average effects of CEPI on water pollution based on a static viewpoint. But the performance of CEPI on water pollution control may also last for a long time (Cheng et al. 2019). Hence, we continue to analyze the dynamic effects of CEPI on water pollution in this part. The results are shown in column (3) in Table 3.

We can see that CEPI is able to reduce PUUSD consistently and significantly, and the reduction effect is further enhanced over time. This finding is different from the previous studies, which have generally assumed that CEI’s policy effects would rapidly fade or even disappear once the policy ends (van Rooij et al. 2017; Kostka and Zhang 2018; Zhao et al. 2020). The reason for the long-term positive effect of CEPI on water pollution control is that CEPI has moved from one-time enforcement to a routinized one (Jia and Chen 2019). Because of this institutionalization of CEPI policy, governments, enterprises, and individuals face long-term pressure from environmental inspections. As a result, local governments will adopt more stringent environmental regulations to avoid environmental quality problems; enterprises will improve their existing extensive production modes and consciously reduce emissions; and the public will become more concerned about environmental issues (Jia and Chen 2019).

** Threats to baseline results and robustness checks**

To ensure that our above findings are reliable, we performed additional robustness checks to rule out the threats of some interference factors on the empirical results. Specifically, the robustness checks include a common trend hypothesis test, an expectation effect test, a placebo test, excluding the interference of other policies, and adopting the propensity score matching and the difference-in-differences (PSM-DID) method.

**Common trend hypothesis test**

The premise of using the DID approach to identify causal effects between CEPI and PUUSD is whether the CEPI and non-CEPI cities meet the common trend hypothesis. We need to ensure that the PUUSD in CEPI and non-CEPI cities are parallel before the CEPI implementation. In that way, we can take the non-CEPI cities as the counterfactual results of CEPI cities after the CEPI implementation and thus accurately obtain the improved performance of CEPI on PUUSD. Figure 2 reports the test results of the common trend hypothesis. We find that each year’s estimated coefficients before CEPI implementation are not significant at the 90% significance level. This suggests that CEPI and non-CEPI cities have the same trend in PUUSD before 2016, satisfying the common trend hypothesis.

**Expectation effect test**

CEPI was formally started in 2016, but as early as July 2015, the Chinese government reviewed and approved the “Environmental Protection Inspection Program (Trial),” which clearly established the mechanism of CEPI. As a result, local governments may have anticipated the implementation of CEPI and adjusted their environmental management accordingly in advance. For this purpose, we draw on the method of Lu et al. (2017) to test whether local governments have expectations for CEPI. The specific approach is to add new interaction terms Treatment × post2014 and Treatment × post2015 in model (1). The results (see Appendix Table 7) find that the coefficients for Treatment × post2014 and Treatment × post2015 are not significant, but the core explanatory variable CEPI is still significantly negative. Thus, there is no significant expected effect until CEPI is officially launched.

**Placebo test**

To exclude the influence of some unobservable factors on CEPI’s water pollution control performance, we further performed two placebo tests on the benchmark model.

One placebo test is based on counterfactual time. We construct spurious CEPI implementation times through advancing CEPI implementation years by 1, 2, and 3 years. Suppose the coefficients of CEPI are not significant, suggesting that the reduction in PUUSD is indeed caused by CEPI. In that case, one can rule out the interference from other factors before CEPI occurred. The regression results (see Appendix Table 8) find that none of the coefficients of CEPI are significant, which essentially allows us to exclude the interference of other factors before the CEPI occurred. This goes some way towards proving the robustness of the baseline regression result.

Another placebo test is based on the fictitious sample. Following Ferrara et al. (2012) and Fang et al. (2019), we randomly select 104 samples from a sample of 500 as spurious CEPI cities and the remaining samples as non-CEPI cities for regression. To increase reliability, we repeat the above random selection steps 500 times. Figure 3 reports the estimated coefficient probability density distribution. We can find that the estimated coefficients
are all centrally distributed at zero, while the baseline result ($-0.207$) is far from the center distribution. This result indicates that CEPI indeed causes the reduction in PUUSD and other random factors are unlikely to influence the basic conclusion.

**Excluding the impact of other policies**

Considering that there may be other policies related to water pollution control in the period of CEPI implementation, the impact of CEPI on water pollution may be interfered. To address this issue, we need to exclude further the interference of these policies to perform robustness tests. Through the search, we found three policies, Environmental Protection Interview (EPI), Five-Year Plan (FYP), and CEPI “retrospective,” which occurred during the same period of our study sample, would interfere with our result and need to be excluded.

First, the EPI, initiated by China’s Ministry of Ecology and Environment in May 2014, aims to urge the government to deal with serious environmental problems and thus will have an impact on water pollution control. Until 2018, a total of 23 cities have implemented EPI for water pollution issues. Therefore, we excluded these 23 cities from the total sample to remove EPI’s interference on the study result.

Second, the Chinese central government had mandated a binding pollutant reduction target for each province during 11th FYP, 12th FYP, and 13 FYP and included these pollutant reduction targets in the performance appraisal.
of local officials as a means to reduce pollutant emissions (Kahn et al. 2015). These three FYPs may interfere with our result. To this end, we refer to the approach of Li et al. (2016) to exclude the interference of FYPs by controlling for the pollutant reduction targets in each province in the baseline regression model.

Third, to check the rectification status of CEPI in each province, the Chinese government launched the CEPI “retrospective” in 2018 in some CEPI cities, which may threaten our baseline results. For this reason, this paper deletes the sample in 2018 and regresses only on the data from 2009 to 2017. If the policy effect of CEPI is still significant after deleting the 2018 data, then it indicates that our baseline result is robust and that CEPI is indeed effective in controlling water pollution.

The results (see Appendix Table 9) show that the sign and significance of CEPI do not differ from the baseline regression result in all columns, indicating that our baseline result is not affected by other policies.

PSM-DID method

The CEPI and non-CEPI cities may have systematic differences before the CEPI implementation, thus leading to a potential sample selectivity bias problem. The PSM method can effectively solve sample selectivity bias, so we use the PSM-DID method to test the robustness of the baseline regression result. Specifically, first, we use the policy group dummy variable Treatment, to perform logit regression on the control variable to obtain the propensity score value. Second, the methods of radius matching, kernel matching, and nearest-neighbor matching were performed to match the non-CEPI cities, respectively. Finally, we evaluate the policy performance of CEPI on improving water pollution based on matched CEPI cities and non-CEPI cities. The results (see Appendix Table 10) show that the PSM-DID estimates are essentially identical to the baseline regression result regardless of the matching method used, which further arguing for the robustness of our baseline regression result, indicating that CEPI does significantly reduce wastewater discharge.

Benefits and costs of CEPI

In this section, we conduct a calculation to estimate the benefits and costs of CEPI based on the water pollution effect estimation results. This preliminary analysis provides an understanding of the range and magnitude of the benefits and costs of using CEPI in tackling the pollution problem. Figure 4 shows the measurement of the costs and benefits of CEPI. The reduction in mortality and morbidity caused by the improvement in water quality is used to measure the benefits, while the losses of GDP caused by CEPI are used to measure the costs.

CEPI benefits: the health benefits from the reduction of mortality and morbidity

In the previous analysis, we have found that the CEPI decreased untreated wastewater discharge by 20.7%. A large body of medical and epidemiological literature has confirmed that the reduction in wastewater discharge is beneficial to human health (Schwarzenbach et al. 2010; Wang and Yang 2016; Landrigan et al. 2018), such as decreasing infant mortality (He and Perloff 2016; Mettetal 2019), lowering cancer morbidity and mortality (Ebenstein 2012; Zhang et al. 2014). Therefore, we measure the health benefits of CEPI by estimating the reduction in mortality and morbidity caused by the decline in water quality.

Firstly, we estimate the health benefits of CEPI on mortality, including infant mortality and digestive cancer mortality. There are three steps for this estimation.

1. We associate the volume of untreated wastewater discharge with water quality grade since previous literature often calculates health benefits based on water quality grade. Ebenstein (2012) found that a 10% increase in untreated wastewater discharge can result in a 0.022 unit increase in water quality grade. Combined with the baseline result in column (2) of Table 3 (20.7%), we can obtain that CEPI can improve water quality grade by 0.046 (2.07 × 0.022 = 0.046) grades.

2. We estimate the infant mortality reduction of CEPI based on water quality grade improvement. As for the
health benefits of infant mortality reduction. He and Perloff (2016) have estimated that one-grade improvement in water quality leads to a 0.6% reduction in infant mortality.\(^3\) With this conclusion, we can calculate that CEPI can reduce infant mortality by approximately 0.028% (0.6% × 0.046 = 0.028%). Further, based on China Health and Family Planning Development Statistics Bulletin, the number of new births in China in 2015 was 16.55 million; thus, we can calculate that CEPI can save the lives of 4,634 (16,550,000 × 0.028% = 4,634) babies.

(3) We calculate the health benefits by monetizing the reduction in deaths using the value of a statistical life (VSL), which is the amount of people’s willingness to pay (WTP) for a marginal reduction in the risk of dying from a given risk factor (OECD 2012). Based on the finding of Miller (2000), who has estimated that the VSL is at least 142 times the GDP per capita in China. The VSL is $1,107,600 based on China’s per capita GDP of $7,800 in 2015. We ultimately calculate that the health benefits of infant mortality reduction due to CEPI are $5.13 billion (1,107,600 × 4,634 = 5.13 × 10^9). As for the health benefits of declining digestive cancer mortality, Ebenstein (2012) has found that one-grade improvement in water quality can decrease digestive cancer mortality by 9.7%. Further, based on the data that approximately 1 million people in China die of digestive cancer in 2015,\(^4\) we can estimate that CEPI can reduce the number of deaths from digestive cancer in China by approximately 4,462 people (1,000,000 × 9.7% × 0.046 = 4,462), which could result in the health benefits of $4.92 billion (1,107,600 × 4,462 = 4.92 × 10^9). Thus, the total benefits of CEPI on mortality are $10.05 billion (5.13 × 10^9 + 4.92 × 10^9 = 10.05 × 10^9).

Secondly, we estimate the health benefits of CEPI on morbidity in China. Relevant studies have shown that the costs of morbidity in China are roughly 22–78% of mortality costs (World Bank 2007). Therefore, we can calculate that the morbidity benefits attributable to CEPI are at least $2.21 billion (22% × 10.05 × 10^9 = 2.21 × 10^9) based on the lower limit of 22%.

In Table 4, we synthesize the above analysis and calculated the health benefits from water quality improvement by CEPI. The results show that the mortality and morbidity benefits resulting from CEPI amount to $12.26 billion (10.05 × 10^9 + 2.21 × 10^9 = 12.26 × 10^9). These benefits are primarily enjoyed by the public, especially those whose health will be damaged due to infant mortality and digestive cancer mortality caused by CEPI. Fan and He (2019) found that nearly half of the rural population in China do not have access to piped water and have to rely on surface water for daily consumption. Water pollution problems would directly threaten the health of these rural populations, especially infants and digestive cancer patients (He and Perloff 2016). Therefore, these groups stand to gain greater health benefits after CEPI improves water quality.

**CEPI costs: the costs from the losses of economy**

Strict environmental regulations may have some negative impact on the economy while improving the environment (Wang and Feng 2014). We calculate the costs of CEPI from two aspects.

First, we explore the impact of CEPI on industrial value. Enterprises have has always been the inspection focus of CEPI. According to relevant reports, enterprises’ pollution problems have been the main content of public complaints, accounting for more than half of the total number of complaints. And, facing the pressure from inspection teams, the most common and direct approach of local governments is to close down many polluting enterprises and factories. For example, in Shandong province, China, more than 100 companies with “poor” safety ratings for the transformation and upgrading of the chemical industry have been shut down. We use the decrease of China’s secondary industry added value to estimate the costs caused by CEPI. These costs are mainly borne by the industrial companies affected by CEPI. Second, we also estimate the impact of CEPI on the Gross domestic product (GDP).

\(^{3}\) It should be noted that in the study of He and Perloff (2016), the relationship between changes in water quality grades and infant mortality was nonlinear, which is “If water quality changes from type I or II to type III, the infant mortality rate will increase by about 6.0 per thousand. Changing water quality from type III to type IV decreases the infant mortality rate by 7.9 per thousand, if water quality deteriorates from type III to type VI, the infant mortality rate drops by 20.2 per thousand.” However, in this paper, we calculate the decrease of infant mortality based on the assumption that the water quality is improved from type III to type I or II, that is a one-grade improvement in water quality leads to a 0.6% reduction in infant mortality. The rationality for our assumption is as follows. First, according to the Chinese authorities, the water quality is divided into six grades (from type I to type VI). The type I water is the best, while type VI is the worst, and only type I to type III water can be used as drinking water. In China, 80% of surface waters are type I to III; thus, the possibility of water quality decreasing from type III to type IV, V, or VI is low. Second, even when the water quality deteriorates severely (worse than type III water), people can notice the change by sight, smell, etc., so they will not drink the water. And thus the infant mortality will not be affected.

\(^{4}\) Cancer Report in China, 2019.
To accurately measure the costs of CEPI in the economy, we used the DID method to perform the evaluation. The specific form is as follows:

\[ Y_{it} = \rho_0 + \rho_1 CEPI_{it} + \gamma Treatment_{i} \times T + \left( C_{it} \times f(T) \right) + \mu_i + \lambda_t + \epsilon_{it} \]  

where, \( Y_{it} \) is the GDP and the secondary industry added value of city \( i \) in year \( t \). The data is obtained from China City Statistical Yearbook. To obey the normal distribution, the indicator \( Y_{it} \) is logarithmized.

The results are shown in Table 5. We find that CEPI reduces the industrial value by 7.7%, while the effect of CEPI on GDP is not significant. These results indicate that although CEPI has an impact on the industry, it does not have a significant negative effect on the economy as a whole. Therefore, we can conclude that CEPI does not cause significant economic losses.

The possible reason for this result is CEPI can promote the green development of enterprises and accelerate their green transformation by eliminating outdated production capacity, and the short-term losses of industrial output caused by CEPI can be transformed into long-term green production power (Tu et al. 2020). For example, an enterprise in Baoji, Shaanxi province was ceased operations for rectification due to CEPI. However, after the renovation, the company eliminated many outdated production equipment and turned it into green production. Therefore, the costs are mainly borne by the industrial companies affected by CEPI, but this burden does not exist for the economy as a whole.

### Potential biases of cost–benefit analysis

One should explain the benefits and costs estimates above with attention that the benefits of CEPI may be underestimated because of some potential biases. To better understand these potential biases, in this section, we present detailed explanations. There are three main reasons the calculation in Table 4 may underestimate the authentic benefits of CEPI.

First, we only calculate the health benefits attributable to the improvement of water quality by CEPI. CEPI is a comprehensive environmental governance policy, and its effects are not only in water quality but also in air and soil, etc. Several studies have also empirically examined the performance of CEPI on air pollution control (Jia and Chen 2019; Wang et al. 2021c; Xu et al. 2020). But given that this paper focuses on the water pollution aspect, it does not include other aspects of environmental performance, such as air and soil, in our results. Therefore, an estimate restricted to water pollution would take only a modest fraction of the total benefits from CEPI.

Second, in calculating the health benefits from improving water quality, we only calculate the mortality and morbidity benefits in infants and digestive cancer. Previous

### Table 4 The benefits of CEPI

| CEPI | WQG | IM | DCM | Benefits of mortality | Benefits of morbidity | Total benefits |
|------|-----|----|-----|-----------------------|-----------------------|---------------|
| 0.207| 0.220| 0.006| 0.097| (1)×(2)×(3)×(16,550,000)×VSL |\( \frac{1107600}{10.05 \text{ billion}} \) |\( 12.26 \text{ billion} \) |

Note: In column (1), we report the relationship between CEPI and PUUSD (see Table 3). In column (2), we report the relationship between water quality grade (WQG) and PUUSD as in Ebenstein (2012). In column (3), we report the relationship between infant mortality (IM) and WQG as in He and Perloff (2016). In column (4), we report the relationship between digestive cancer mortality (DCM) and WQG as in Ebenstein (2012). In column (5), we calculate the mortality benefits based on the VSL of $1,107,600 (in 2015). In column (6), we calculate the morbidity benefit based on the lower limit of 22% of the mortality benefit in China as in Landrigan et al. (2018). In column (7), we report the total benefits of CEPI to improve water quality

### Table 5 The average effect of CEPI on industrial value and GDP

| CEPI | GDP |
|------|-----|
| −0.077** (0.033) | −0.010 (0.017) |
| 0.974 | 0.986 |
| 4961 | 4977 |

(1) The regression controls for Treatment trend, Control \( \times T \), Control \( \times T^2 \), Control \( \times T^3 \), Year fixed effect, and City fixed effect.
(2) Robust standard errors clustered at the city level are reported in parentheses; ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.
studies have shown that water pollution can cause not only digestive cancer but also other waterborne diseases, such as acute diarrhea, Legionnaires’ disease, and typhoid fever (Schwarzenbach et al. 2010). However, due to data problems, these correlative water quality benefits cannot be obtained in our calculation and will make our measurement an understatement of the total CEPI benefits.

Third, the paper only calculates the direct health benefits attributable to CEPI while neglecting the indirect benefits, such as improving the government’s enforcement ability and public environmental participation (Quan 2020). These indirect benefits can also contribute to the total benefits of CEPI through different forms.

In sum, a conservative estimation is that CEPI can generate at least $12.26 billion in health benefits, without incurring significant economic costs. And after considering the potential biases, the benefits of CEPI will be further improved, the gap between the benefits and costs will widen even more, and the cost–benefit ratio of CEPI will be further improved.

Mechanisms: WHY CEPI is cost-effective?

Theoretical analysis of the mechanism of CEPI

The empirical analyses in the previous sections indicate that CEPI is effective in controlling water pollution, whether in the short term or in the long term, and thus the health benefits of CEPI are larger than the costs. However, there is an essential question as to the working mechanism of CEPI to reduce water pollution and thus become cost-effective. Based on previous literature, we propose there are three mechanisms, as shown in Fig. 5.

First, CEPI has a deterrent effect on local officials and forces them to deal with water pollution. In the past, the local governments tend to put economic growth in the first place (Chow 2010). However, CEPI has changed this situation, prompting the local governments to make environmental protection as their immediate priority (Jia and Chen 2019). Local party committees and governments have become the main inspection targets of CEPI. Government officials with unfavorable supervision and lax law enforcement will be interviewed and held accountable. As Table 1 in the “Background” section shows, approximately 18,000 local officials were interviewed and held accountable during the inspection period, many of whom were senior-level local officials. This has brought a strong deterrent effect on other officials, thus greatly increasing local governments’ enforcement efforts and forcing them to implement environmental protection policies seriously and earnestly.

Second, CEPI has a penalty effect on enterprises. CEPI aims to reduce pollution through fining polluting enterprises, controlling their production, and forcing them to eliminate some outdated production equipment (van der Kamp 2017). Through these measures, the enterprises are forced to comply with environmental laws and regulations, which in turn reduces environmental pollution. Meanwhile, the penalty on polluted enterprises enhances the reputation of the regulator and will have a magnified punishment effect on other firms (Shimshack and Ward 2005).

Third, CEPI can enhance public participation in environmental governance. Public participation plays an important role in controlling environmental pollution (Wang and Di 2002). Lorentzen et al. (2014) and Xu et al. (2020) pointed out that public participation can create a bottom-up monitoring approach to discipline local governments, which significantly alleviates the severe information asymmetry that exists between central and local governments and pushes local governments to improve their environmental performance. During CEPI, public complaint channels are opened, and the public is encouraged to provide environmental clues to the inspection team through phone calls, letters, and emails. The local governments are also required to provide timely feedback and disclose information on the public complaints they received. In addition, during the inspection period, the CEPI team will also select some letters to re-examine...
and verify local governments’ response to the complaint letters, and officials who give inconsistent feedback will be directly held accountable. Through these measures, the governments can vigorously strengthen public participation in environmental protection and raise public awareness and enthusiasm for environmental protection (Jia and Chen 2019).

### Empirical analysis of the mechanism

In this section, we use the three-step approach proposed by Baron and Kenny (1986) to examine the above three mechanisms empirically. The specific models are as follows:

\[
PUUSD_{it} = \alpha_0 + \alpha_1 CEPI_{it} + \gamma \text{Treatment}_{it} \times T + \left(C_{it} \times f(T)\right) \theta + \mu_i + \lambda_t + \epsilon_{it}
\]  

(4)

\[
M_{it} = \tau_0 + \tau_1 CEPI_{it} + \gamma \text{Treatment}_{it} \times T + \left(C_{it} \times f(T)\right) \theta + \mu_i + \lambda_t + \epsilon_{it}
\]  

(5)

\[
PUUSD_{it} = \varphi_0 + \varphi_1 CEPI_{it} + \varphi_2 M_{it} + \gamma \text{Treatment}_{it} \times T + \left(C_{it} \times f(T)\right) \theta + \mu_i + \lambda_t + \epsilon_{it}
\]  

(6)

where \(M_{it}\) represents the three different mechanism variables mentioned in the previous sub-section. Following Deng et al. (2021), we use the number of times local governments examining enterprises each year (Examine) to measure the deterrent effect of CEPI on local officials; the amount of fines (Fine) to measure the penalty effect of CEPI on enterprises; and the number of public complaints (Complaint) to measure the degree of public participation. However, we can only obtain the above three mechanism indicators at the provincial level. Based on the method of Fan and Zhao (2019), we use the proportion of the city’s industrial output to the provincial industrial output as the weight and multiply it by Examine, Fine, and Complaint to obtain the city-level data we need. Examine, Fine, and Complaint are treated as natural logarithms. \(\alpha_i\) represents the total effect of CEPI on water pollution, \(\varphi_1\) shows the direct effect of CEPI on water pollution, and \(\tau_1 \times \varphi_2\) is the indirect effect of CEPI on water pollution. If both \(\varphi_1\) and \(\varphi_2\) are significant and the sign of \(\varphi_1 \times \varphi_2\) is consistent with \(\alpha_i\), it proves that the mediating effect is established.

The results are shown in Table 6. Column (1) reports the total effect of CEPI on water pollution. The result is consistent with the baseline results showing that CEPI has a significant negative impact on water pollution. Columns (2) and (3) demonstrate the analysis results of the deterrent effect. We can find that the coefficient of CEPI is significantly positive in column (2) and the coefficient of
Examine is significantly negative in column (3), indicating that CEPI can reduce water pollution by increasing the number of inspections launched by local governments. The same results are obtained in columns (4) and (5) and columns (6) and (7). The results of columns (4) and (5) show that CEPI can reduce water pollution by increasing fines for polluting enterprises. The results of columns (6) and (7) prove that CEPI can reduce water pollution by increasing the number of public complaints. So, the three mechanisms of CEPI to reduce water pollution have been well demonstrated.

**Conclusion**

As an important means of environmental governance, CEI is always criticized for its high cost. The CEPI provides a good opportunity for us to study the benefits and costs of CEI. Based on annual panel data from 500 cities during 2009–2018, we regard the CEPI as a quasi-natural experiment and use the DID method to perform a rough calculation to compare the benefits and costs of CEPI based on the water pollution effect estimates of CEPI on water pollution. Our empirical results show that, first, CEPI has led to an average 20.7% reduction in water pollution, and this effect remained significant in the long term. A series of robustness checks demonstrate that this baseline result is reliable. Second, the benefits and costs estimation results indicate that the total health benefits from the reduction in mortality and morbidity attributable to CEPI amount to $12.26 billion and that CEPI does not have a negative impact on the economy. After considering potential biases, the benefits of CEPI would be further expanded. Third, the analysis of the mechanisms shows that CEPI reduces water pollution and becomes cost-effective mainly through deterring local officials, punishing polluting enterprises, and increasing public participation.

Based on the above findings, the policy implications of this paper are as follows.

First, the government should continue to promote the normalization of the CEPI system vigorously. From the cost–benefit analysis results, although CEPI has caused certain costs, it can also bring greater benefits to society. CEPI can not only reduce the pollutant emissions of enterprises and eliminate outdated production capacity but also restrain local officials from inaction and harboring polluting enterprises, thus improving environmental quality and promoting green economic development. Therefore, in the following inspection, the central government can work in various ways, such as organizing periodic spot checks, conducting special inspections and CEPI “retrospective,” and crackdown on undesirable phenomena such as “superficial rectification,” “perfunctory rectification,” and “one-size-fits-all,” to make environmental governance have long-term performance.

Second, the government should strengthen citizens’ awareness of environmental protection, open multi-channel reporting platforms, and improve bottom-up environmental monitoring systems. Water pollution is closely related to citizens’ lives, and their environmental awareness, attitudes, and perceptions of environmental risks will directly or indirectly influence local governments’ environmental governance (Wang and Watanabe 2019). The government should transmit the harms caused by environmental problems to the public through various mediums, such as TV, the Internet, media, and newspapers, to raise citizens’ environmental awareness. The government should also liberalize multiple reporting channels and conduct strict verification, quick processing, and timely feedback on environmental problems reported by citizens, thus forming a bottom-up inspection mechanism to discipline the environmental behavior of local governments.

Third, the government should adopt high-tech means and innovating inspection methods. The asymmetry of pollution information is a major obstacle in environmental governance. The government can establish the central ecological and environmental protection inspection information system and increase the application of technologies, such as satellite remote sensing, infrared identification, drones, and big data, to find environmental problems and improve environmental governance.

In addition, due to the lack of data on wastewater quality indicators (WQI) at the city level (including prefecture and county level), such as chemical oxygen demand, phosphate, and total nitrogen, we are unable to directly assess the impact of CEPI on these WQI. If detailed information about these WQI were available, we could estimate the changes in various WQI under the effect of CEPI and thus analyze the governance behavior of local governments.
## Appendix

### Table 7  Expectation effect test

|                  | (1)                  | (2)                  | (3)                  |
|------------------|----------------------|----------------------|----------------------|
| CEPI             | $-0.195(0.117)$     | $-0.239^{**}(0.105)$ | $-0.223^{**}(0.107)$ |
| Treatment$\times$post$_{2014}$ | 0.090(0.112)        |                      | 0.065(0.105)         |
| Treatment$\times$post$_{2015}$ |                      | 0.097(0.099)        | 0.076(0.089)         |
| $R^2$            | 0.673                | 0.673                | 0.673                |
| $N$              | 4743                 | 4743                 | 4743                 |

(1) The regression controls for Treatment trend, Control$ \times T$, Control$ \times T^2$, Control$ \times T^3$. Year fixed effect, and City fixed effect. (2) Robust standard errors clustered at the city level are reported in parentheses; "***", "**", and "*" indicate statistical significance at 1%, 5%, and 10%, respectively.

### Table 8  Placebo test: advancing the time of CEPI implementation

|                  | One year in advance | Two years in advance | Three years in advance |
|------------------|---------------------|----------------------|------------------------|
| CEPI$_{2015}$    | 0.008(0.111)        |                      |                        |
| CEPI$_{2014}$    |                     | 0.124(0.107)        |                        |
| CEPI$_{2013}$    |                     |                      | 0.068(0.124)          |
| $R^2$            | 0.673               | 0.673                | 0.678                  |
| $N$              | 4743                | 4743                 | 4277                   |

(1) The regression controls for Treatment trend, Control$ \times T$, Control$ \times T^2$, Control$ \times T^3$. Year fixed effect, and City fixed effect. (2) Robust standard errors clustered at the city level are reported in parentheses; "***", "**", and "*" indicate statistical significance at 1%, 5%, and 10%, respectively.

### Table 9  Robustness test: Excluding other policies

|                  | (1)                          | (2)                          | (3)                          |
|------------------|------------------------------|------------------------------|------------------------------|
| CEPI             | $-0.184^{*}(0.097)$         | $-0.202^{**}(0.096)$        | $-0.184^{*}(0.100)$         |
| $R^2$            | 0.667                        | 0.674                        | 0.678                        |
| $N$              | 4585                         | 4743                         | 4277                         |

(1) The regression controls for Treatment trend, Control$ \times T$, Control$ \times T^2$, Control$ \times T^3$. Year fixed effect, and City fixed effect. (2) Robust standard errors clustered at the city level are reported in parentheses; "***", "**", and "*" indicate statistical significance at 1%, 5%, and 10%, respectively.

### Table 10  Robustness test: PSM-DID

|                  | Radius matching | Kernel matching | Nearest-neighbor matching |
|------------------|-----------------|-----------------|--------------------------|
| CEPI             | $-0.222^{*}(0.131)$ | $-0.209^{*}(0.114)$ | $-0.224^{*}(0.131)$     |
| $R^2$            | 0.719            | 0.672            | 0.720                     |
| $N$              | 2827             | 4738             | 2831                      |

(1) The regression controls for Treatment trend, Control$ \times T$, Control$ \times T^2$, Control$ \times T^3$. Year fixed effect, and City fixed effect. (2) Robust standard errors clustered at the city level are reported in parentheses; "***", "**", and "*" indicate statistical significance at 1%, 5%, and 10%, respectively.
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Data availability The data used to support the findings of this study are available from the corresponding author upon request.

Declarations

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