Inspectors Come and Go:

Strategic Responses to Central Environmental Protection Inspection Revealed by Production Electricity Consumption

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preliminary version and not well polished

This paper examines whether localities are strategic responses to the announced-to-be-regularized central environmental protection inspection (CEPI) by using high-frequency production-side electricity consumption data. We demonstrate that by conniving at overproduction before the arrival of the inspection and restricting production during the on-site inspection, the localities achieve the gain of avoiding economic losses and political non-compliance at the same time. Once the inspector leaves, production activities rebound immediately and even exceed the pre-inspection level. The response patterns provide by air quality data are relatively noisy and are one-week lags to production activities. Industry-level evidence implies that the in-advance overproduction is dominated by industrial sectors and is more pronounced in light industrial sectors within the secondary industry. Restrictions on production and rebounds effect are prevalent in all industries but differ in magnitude. The incentive and capacity of the local government to collude with enterprises are essential determinants of strategic response. There are weaker strategic responses when the party secretary or mayor is closer to retirement or has a higher likelihood of promotion. From the government-business relationship, the local government with a lower cleanliness level can strongly mobilize enterprises to adjust production systematically. While the cordial government dedicated to providing corruption-free business assistance is less authority in making enterprises comply with arrangements.

Keywords: Central environmental protection inspection (CEPI), Second round, Air quality, Electricity usage, Industry heterogeneity, Government-business relationship

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1. Introduction

How to balance economic growth and environmental quality has long been an important policy issue (Grossman & Krueger, 1995; Stern, 2004). As one of the fastest-growing economies in the last decades, China has transitioned from rapid growth to high-quality development. In the new development era, ecological civilization has been one of the most important goals pursued by the Chinese government, for environmental quality is intimately related to the well-being of people (Lai, 2017; Zhang et al., 2017). The environmental governance system in China is decentralized, and information asymmetry between the central and local governments leads to inefficient top-down efforts to improve environmental quality (Ghanem & Zhang, 2014; Greenstone et al., 2022). To address the principal-agent problem, the central government innovatively launched the central environmental protection inspection (CEPI) system in 2015 (see Section 2.1 for a detailed introduction to the development of CEPI). The CEPI is highly politically authoritative, with inspection teams headed by high-hierarchy central officials stationed in all 31 provinces in different batches. The inspection results and subsequent rectifications are directly associated with local officials' political prospects.

From the number of complaints received from the public, the number of officials held accountable, and fines imposed on pollution enterprises, the first round of CEPI conducted from 2016 to 2017 has made significant results (see Appendix Table A1 for the detailed schedule of the first round of CEPI). However, many studies suspect localities may cope with the inspection through the "one-size-fits-all" approach, such as restriction or shutdown production (see Section 2.2 for a detailed review of these studies). If the strategic responses do exist, the environmental improvement brought by CEPI may be unsustainable.

Nevertheless, the existing literature may face the following shortcomings. First, the outcome of these studies is almost air quality, which is regarded as the proxy for production activities. Since it takes time for air pollutants from generation to be captured by a monitor, the real-time air quality indicators may not reflect simultaneous production behavior, which may lead to biased estimates of the CEPI effect. Since the inspection targets not only air pollution but also cover water, soil, urban, and other pollution, the indirect analysis focus on air quality cannot describe how various sectors respond heterogeneously to the inspection. Second, the existing studies focus on the effect of the first round of CEPI. After finishing the first round of CEPI, the central government announced that the inspection would be regularized and conducted every five years. It raises a new question about whether localities still respond strategically when the inspection becomes a repeated game. Some theoretical studies provide insights into that (Myerson, 1979; Radner, 1985), but there is still a lack of evidence provided by empirical examinations. Third, the economic agents that lead to CEPI-air quality patterns observed in previous studies are unclear. As the main subject of the inspection is the local government, we can expect the important role played by the local government in causing strategic responses. Clarifying the issue is essential for policymakers to adopt effective initiatives.

To fill these gaps, this paper exploits novel production-side electricity consumption data of counties in two provinces, Zhejiang and Jiangsu, to explore how production activities strategically respond to the second round of CEPI. The second round of CEPI was carried out in Zhejiang from September 1, 2020, to October 1, 2020, and later in Jiangsu, from March 25, 2022, to April 25, 2022. We use high-frequency electricity consumption data at the county-industry-daily level and combine the one-size-fits-all difference-in-difference design proposed by Fu & Gu (2017) to estimate the policy effects of CEPI in various stages. Following Karplus & Wu (2019), we assign 7-12 weeks before the arrival of on-site inspection as reference weeks, 1-6 weeks before the arrival of CEPI as the announcement period, 0-3 weeks after the arrival of the inspectors as the on-site inspection period, and 4-6 weeks after the arrival of CEPI as the post-inspection period. We include the electricity data for the same date in the previous year before the arrival of the inspection team in the model to remove the seasonality of production orthogonal to the implementation of CEPI. We also control for weather conditions, including temperature, precipitation, wind speed, humidity, and air pressure. We use the cumulative number of confirmed COVID-19 cases to mitigate the influence of COVID-19 outbreaks during the sample period. The fourth-order polynomial is used to control for the time trend. We also control for county-by-year and city-by-month fixed effects flexibly.

We first examine whether electricity consumption is a plausible proxy for production activities. Since nighttime light is widely used to reflect economic activities (Chen & Nordhaus, 2011; Henderson et al., 2012), we examine the relationship between electricity consumption and nighttime light using VIIRS data. Our results show that they are significantly correlated, with a 1% increase in electricity consumption associated with a 0.25% increase in nighttime light intensity, indicating the validity of the electricity consumption data. We then explore the strategic response of production to the second round of CEPI. We find that the weekly electricity consumption increased by 7.9% on average during the announcement period, compared to reference weeks. Once the inspection arrives, the electricity usage declines immediately and is 15.5% lower on average during the on-site inspection period compared to the announcement period. Through the strategic production adjustment before and after the arrival of inspectors, localities avoid economic losses and also reduce non-compliance risks. After the inspector leaves, production activities rebound significantly, with an average increase of 8.3% compared to the on-site inspection period. These results reveal that the pollution reduction due to CEPI, as found by previous studies, is more of a short-term improvement in response to political mandates, similar to the Olympic blue (Chen et al., 2013) and the APEC blue (Wang et al., 2016). However, we find that strategic responses are less pronounced for Zhejiang, where the interval between two rounds of CEPI is shorter, suggesting that more frequent inspections help force localities to improve environmental quality essentially. Baseline results are robust after modifying empirical specifications.

We also use air quality indicators, including AQI, PM2.5, and PM10, as outcomes to examine the effect of the second round of CEPI on air quality. However, response patterns presented by air quality are somewhat noisy and inconsistent across indicators. More importantly, the response pattern of air quality is observed one week lag to that of electricity consumption. Considering that air pollutants are captured by monitors after experiencing complex atmospheric processes, the one-week lag suggests that production activities and real-time air quality are not simultaneous, and we should be cautious in interpreting the results with air quality as outcomes.

By industry, the overproduction during the announcement period is mainly dominated by the secondary industry, while the primary sector experienced a slight production reduction. By dividing the tertiary sector into the producer and consumer service sectors, we find patterns of the former are closer to the secondary industry, reflecting the nexus in the production value chain. Further, we conduct the heterogeneity analysis of sub-sectors within the secondary industry. We find overproduction more concentrated in the industrial sectors, such as textiles and leather, where production adjustments are more flexible and less costly. However, production reductions during the on-site inspection period and rebound effects during the post-inspection period are prevalent in all sectors, providing direct evidence that localities still adopt strategic behavior even under the repeated inspection game.

We finally test the role of local governments in inducing such systemically strategic responses. We manually collect biographies of party secretaries and mayors of prefectural cities from official websites and construct two variables to measure the incentives for local leaders to respond strategically to inspection. The first variable is months to their retirement when the inspection begins, and the second variable is months they have served as secretaries or mayors when the inspection begins. In the bureaucracy of China, the longer a leader serves in a position, the higher likelihood of being further promoted. We demonstrate that the strategic response to CEPI is weaker as local leaders get closer to retirement or are more likely to be further promoted, indicating incentives for local leaders are critical in leading to a strategic response. We examine the role of the capacity of local governments to collude with enterprises in inducing a response. Nie et al. (2020) provide two aspects of the government-business relationship index: the closeness and cleanliness index. The closeness index measures the extent to which local governments care about and are eager to provide help to enterprises. The cleanliness index measures the extent to which local governments are corruption-free in their dealings with enterprises. The results show that strategic responses are more often in counties with local governments at a lower level of cleanliness. Local governments with a higher level of closeness are helpful for enterprises' production, but they cannot mobilize enterprises to adjust production systematically to cope with the inspection.

Our paper contributes to the literature from at least the following aspects. First, we enrich the literature that focuses on the effects of central vertical regulation on localities' performance under a decentralized system (Chen et al., 2022b; Karplus & Wu, 2019; Wang et al., 2023; Zhang et al., 2018a). We use high-quality electricity consumption data to provide direct evidence of strategic responses across industries and fill the gap that previous studies are unable to observe high-frequency production changes.

Second, we provide empirical evidence for the principal-agent problem under repeated games (Myerson, 1979; Radner, 1985). In the context of the central environmental inspection of China, we verify that localities still adopt strategic response behaviors when facing regularized, strict, and high authority inspection. This finding implies that the air improvement induced by CEPI in previous studies is more likely to be short-term and can be attributed to a response to political mandates (Chen et al., 2013; Wang et al., 2016).

Third, we highlight the role of local governments in leading to strategic responses. One study similar to this paper is Zou (2021), who finds the use of city air quality warnings increases on monitored days, reflecting the coordinating role of local governments in emission reductions. In this paper, we find that both incentives of local governments and their capacity to collude with enterprises are determinants of strategic response. The systematic overproduction of sub-sectors within the secondary industry during the announcement period can best be explained by the mobilization of local governments, which reflects the role of political forces in adjusting local production plans.

Finally, for the first time, we examine the effect of the second round of CEPI on air quality, while previous studies concentrated on the effects of the first round of CEPI (see the literature review in Section 2.2). However, in a rigorous empirical setting, we find response patterns provided by air quality are relatively noisy and are one week lag to production activities, which reminds us that one should be more cautious when interpreting results that outcomes are air quality. In contrast, the high-frequency electricity data reveal the strategic responses of local governments to the inspection clearly.

The rest of the paper is organized as follows. Section 2 introduces the background and development of the CEPI system, and literature findings on evaluating the effects of the first round of CEPI. Section 3 describes the data and design of the empirical specification. Section 4 presents the main results and explores the mechanisms of strategic responses from the political economy perspective. Section 5 concludes our findings and provides policy implications.

2. Background

2.1 Development of the CEPI System

Environmental governance presents a typical central-local relation problem in China (Kostka & Nahm, 2017). At the beginning of the reform and opening up, China adopted territorial management for environmental pollution prevention and control. As forced by the Environmental Protection Law implemented in 1989, local governments are responsible for the environmental governance of their jurisdictions. Therefore, local governments at all layers established specific institutions for environmental enforcement and supervision work. However, given the promotion of local officials mainly depends on economic performance (Li & Zhou, 2005), local governments have the incentive to sacrifice environmental quality for higher economic growth, known as 'pollution for promotion' (Jia, 2017). The decentralized management system has the shortage that local governments are inefficient in curbing environmental pollution, even though they have more complete information on pollution.

To enhance the supervision of the central government and to coordinate inter-jurisdictional pollution disputes, the State Environmental Protection Administration (SEPA) has established six regional environmental supervision centers since 2006,[2] that is, North, East, South, Northwest, Southwest, and Northeast Centers. The establishment of regional supervision centers achieves the combination of territorial and vertical environmental management. However, regional environmental supervision centers are government-affiliated institutions, which causes them to lack environmental enforcement authority. Under the system arrangement, supervision centers focus on the emission responsibilities of micro-level enterprises and have limited constraints on local governments.

With the coming power of Xi Jinping in 2013, the new central government showed the determination to combat environmental pollution and declared a 'war on pollution' in 2014 (Greenstone et al., 2021). In 2014, the MEP issued the 'Interim Measures for Comprehensive Supervision Work' and the 'Interim Measures for Interviews by the MEP'[3], highlighting the responsibility of local governments in environmental governance and declaring the supervision focus on both enterprise and local government. With the issuance of the 'Environmental Protection Inspector Program (Trial)' by the State Council in August 2015,[4] the central environmental inspection system was officially launched. The Program plans to conduct a round of inspections for 31 provinces every five years since 2016 and is emphasizing the joint responsibility of local governments and party committees. In 2016, the National Environmental Protection Inspector Office, affiliated with the MEP, was established to coordinate the implementation of CEPI. In November 2017, to cooperate with the implementation of CEPI, six regional environmental supervision centers were changed to dispatch administrative agencies by the MEP and were renamed regional inspection bureaus, thereby increasing their enforcement authority.[5]

The CEPI is an innovation in the environmental regulatory system of China. The CEPI team has a high administrative level and enforcement power. The head of the CEPI team is a full ministerial-level official and is appointed by the central government. The deputy head of the team is a deputy

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[2] The SEPA was renamed the Ministry of Environmental Protection (MEP) in 2008, and the MEP was renamed the Ministry of Ecology and Environment (MEE) in 2018. The six environmental supervision centers were formally established in 2008.

[3] They refer to '综合督查工作暂行办法' and '环境保护部约谈暂行办法', respectively.

[4] After finishing the first round of environmental inspectors, the Program was upgraded to 'Central Ecological Environmental Protection Inspectors Work Regulations' (中央生态环境保护督察工作规定), which the State Council issued in June 2019. See: http://www.gov.cn/zhengce/2019-06/17/content_5401085.htm.

[5] Please see the report of People's Daily for more details: http://env.people.com.cn/n1/2017/1123/c1010-29664642.html.

ministerial-level official from the MEE. Other members are also from the core departments of the central government,[6] making the team very similar to the inspector of Imperial China (*Qin Chai*). The first round of CEPI began on January 4, 2016, with Hebei as the pilot province. After the pilot inspection, all 30 provinces are covered by four batches of inspectors from July 2016 to September 2017. We summarize the time of arrival and leave of the inspectors for each province in Appendix Table A1.

The on-site inspection of CEPI in each province lasts for one month, and it can be further roughly divided into three stages with 10 days as the interval. The first ten days are the provincial inspector stage. In this stage, the inspector team interview with provincial and municipal officials, and clarifies the key issues of environmental governance in the province by retrieving and reviewing materials. In addition, the inspectors set up hotlines, letters, and emails to receive complaints from the public, and complaint channels are available during all stages of the inspection. In the second stage, the inspection team conducts a ten-day sinking inspection. During the sinking inspection stage, based on the issues mastered in the first stage, the inspectors investigate prefecture-level cities, counties, and key enterprises to collect first-hand information. Commonly, four to six prefecture-level cities are focus covered in this stage, and other cities are also randomly selected for inspection. In the last stage, the inspection team aggregate and collate the materials and report that to the State Council. After the on-site inspection period, the inspection report is evaluated and approved by the State Council, and then it is transferred to provincial party committees and governments. After that, the provincial government is required to develop a rectification plan and submit it to the State Council within 30 days. Within six months, the provincial government needs to submit the implementation of the rectification status and open it to the public. The results of the inspection and rectification are directly coupled with the assessment and promotion of local officials. It is worth noting that the arrival of the central inspection team is not sudden for local governments. After the members are selected, the provincial government is informed of the inspection plan in advance of four weeks (Li et al., 2022) to six weeks (Karplus & Wu, 2019).

After finishing the routine inspection in the first round of the CEPI, the central government launched the revisit inspection to check the implementation of the rectification. The revisit inspection

[6] These departments include the Central Commission for Discipline Inspection, the Central Organization Department, and the MEE.

was conducted from June to December 2018, with 20 provinces covered by two batches of inspectors. The time of revisit inspection for each province is also listed in Appendix Table A1. The central government started the second round of CEPI on July 11, 2019. However, being affected by the outbreak of COVID-19, the inspection was not fully completed until April 25, 2022. All 31 provinces are covered by six batches of inspectors, and the arrival and leave date of CEPI is presented in Appendix Table A1.

2.2 Review of the First Round of CEPI Effects

Due to the high hierarchy of authority and the combination of encouraging public participation, punishing non-compliant enterprises, and accounting for responsible officials (Deng et al., 2021; Lin et al., 2021), the first round of CEPI has made remarkable achievements. The first round of CEPI, including routine and revisit inspections, has received more than 0.212 million complaints from the public, filed cases against more than 40 thousand enterprises and fined 2.46 billion Yuan, and over 20 thousand officials were held accountable.[7] As campaign-style environmental enforcement, the penalty intensity of CEPI is unprecedented.

Some studies exploit the implementation of the first round of CEPI as a quasi-experiment to identify the causal effects of CEPI on local environmental performance. However, due to the limitation of data availability, the outcome of these studies mainly focuses on air quality. We provide a comprehensive review of these studies in Table 1, all of which use high-frequency air quality data. These studies reveal some similarities regarding the effect of CEPI on air quality. However, details vary widely across studies. From study samples and outcomes, most of them focus on air quality at the city level. Air quality indicators always include Air Quality Index (AQI), PM2.5, and PM10, and some studies also adopt other pollutants- SO2, NO2, CO, and O3. An exception is Karplus & Wu (2019), which analyzes at the coal power plant level., and the outcome is SO2 readings from the nearest monitor of plants. Moreover, most of them focus on the effects of routine inspection, but some studies also evaluate the effect of revisit inspection. These studies systematically indicate that on-site inspection reduces air pollution significantly, while the effects are heterogeneous among pollutants, with the most pronounced for AQI and PMs. Some studies find evidence of advanced actions to cope

[7] For detailed reports, please see: http://www.gov.cn/hudong/2019-05/15/content_5391977.htm, and https://www.chinanews.com.cn/gn/2019/04-23/8816969.shtml.

with CEPI (Tan & Mao, 2021; Yuan et al., 2022), and early effects also vary across pollutants. However, for the rebound effect after the end of CEPI, findings are inconsistent among studies. Some studies confirm that the pollution reduction by CEPI can persist in the long run (Deng et al., 2021; Wang et al., 2019), and even the overall effect of CEPI is dominated by the post-inspection period (Jia & Chen, 2019). Nevertheless, Tan & Mao (2021) and Yuan et al. (2022) find that the air quality rebounds immediately once the inspectors leave, or the rebound effect exists in the medium or long run (Feng et al., 2022; Karplus & Wu, 2019; Zheng & Na, 2020).

These studies employ RDD or staggered DID/ event study methods to evaluate the policy effects of CEPI. However, the validity of these identifications may be questionable. First, many studies see the timing of CEPI as an exogenous shock and use RDD to identify the policy effects. However, both theoretical arguments (Karplus & Wu, 2019; Yuan et al., 2022) and empirical practices (Tan & Mao, 2021; Yuan et al., 2022) indicate that local governments could know the timing of the arrival of CEPI and take action in advance, such as informing pollution-contributing firms in advance to increase their production during the announcement period, thus to reduce the economic losses caused by the inspection. This pattern also appears in our industry-level data, as presented in Table 2. Due to the existence of the expectation, comparisons of air quality around the time cutoff can not reveal the full effect of CEPI, and the sharp RDD is not applicable. Second, some studies use staggered DID or event study methods to evaluate the policy effect with nationwide city samples. However, most of these studies ignore the recent developments in staggered DID design (Athey & Imbens, 2022; Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021), which may lead to biased estimations of CEPI effects. In addition, considering the implementation of CEPI and air quality vary dramatically across cities nationwide, results of these studies are hard to find clear economic interpretations.

To summarize, although previous studies consistently found that on-site inspection contributes to improving air quality, there is no consensus on the existence of advanced actions before the arrival of CEPI or rebound effects after the leave of CEPI. In addition, previous studies do not clarify the economic agents that lead to strategic changes in air quality at different stages of CEPI, and the response heterogeneity across industries and sectors remains unclear.

Table 1: Review of effects of the first round of CEPI on air quality

Study	Sample cities	Time horizon	Outcomes	Identification	Main findings
Deng et al. (2021)	283 cities covered by four batches of routine inspection and two batches of revisit inspection	2014 January 1, 2014, to July 1, 2019	AQI, PM2.5, PM10, NO2, SO2, CO, O3	RDD	(1) implementation of CEPI significantly reduces air quality indexes except for O3, and effects vary across different batches of routine inspection; (2) there is no unique time for all sample cities to take advance action, but the possibility of advance action cannot be ruled out; (3) air quality indexes do not rebound significantly after the CEPI leave, and the pollution reduction effect of CEPI is sustainable in the long-run; (4) the revisit inspection also reduces air pollution, and the effect of the second batch is stronger.
Feng et al. (2022)	86 cities (43 cities that were inspected for air pollution problems as treatment cities,[8] 43 cities that were not inspected for air pollution problems as control cities) covered by four batches of routine inspection and the first batch of revisit inspection	January 1, 2015, to December 31, 2018	AQI, PM2.5, PM10, NO2, SO2	staggered DID	(1) all air quality indexes decrease significantly in treatment cities compared to control cities after the routine inspection; the pollution reduction effect is significant in all four batches of routine inspection and is gradually increased; (2) the revisit inspection also decreases all air quality indexes; (3) the effect of the routine inspection rebounds after the CEPI leaves, which even exceeds the pre-inspection level after nine months after the CEPI leaves; (4) the effect of revisit inspection also gradually rebounds after the CEPI leaves and backs to the pre-inspection level after six months after the CEPI leaves;
Jia & Chen (2019)	355 cities covered by the first and second batches of routine inspection	July 11, 2014, to April 23, 2017	AQI, PM2.5, PM10, NO2, SO2, CO, O3; but mainly focus on	staggered DID	(1) CEPI significantly reduces air pollution, but the effect is dominated by post-CEPI periods; (2) during the on-site inspection period, AQI increases significantly, coefficient of PM2.5 is also positive but not

[8] In Feng et al. (2022), if air pollution problems in a city are pointed out in the *Rectification Plan for Feedback of Central Environmental Inspection*, the city is assigned as a treatment city.

			AQI and PM2.5		significant; (3) air quality begins to improve significantly after 3-4 months after the CEPI leaves, and the effect persists in the long-run, 5-8 months after the CEPI leaves.
Karplus & Wu (2019)	973 coal power plants in 89 cities of six provinces (Hebei, Henan, Hubei, Guangdong, Shanxi, and Shandong) covered by four batches of routine inspection	May 2014 to May 2018	SO2 readings from the nearest monitor of plants	entropy-balanced event study	(1) SO2 changes insignificantly during the announcement period (1-6 weeks before CEPI arrives); (2) SO2 decreases significantly during the on-site inspection period (0-3 weeks after CEPI arrives); (3) SO2 still decreases significantly after the leave of CEPI in the short-run (0-12 weeks after CEPI leaves) but rebounds significantly in the long-run (24-36 weeks after CEPI leaves).
Lin et al. (2021)	291 cities covered by four batches of routine inspection	January 1, 2015, to May 31, 2018	AQI, PM2.5, PM10, NO2, SO2, CO, O3	staggered DID	implementation of CEPI significantly reduces AQI, PM2.5, PM10, SO2, NO2, and significantly increases O3. CEPI has no significant effect on CO.
Tan & Mao (2021)	286 cities covered by four batches of routine inspection	July 1, 2015, to March 15, 2018	AQI, PM2.5, PM10, NO2, SO2, CO, O3	RDD	(1) implementation of CEPI significantly reduces AQI, PM2.5, PM10, and SO2, but has no significant effect on CO, NO2, and O3; (2) there is evidence of advanced action, and early effects vary across different pollutants; PM10 increases as early as three weeks before the CEPI arrives, and early decrease effects for CO and NO2 appear up to 4-6 weeks before the on-site inspection; (3) the pollution reduction effect rebounds immediately after the end of the on-site inspection.
Wang et al. (2019)	288 cities covered by four batches of routine inspection and the first batch of revisit inspection	September 1, 2015, to August 31, 2018	AQI, PM2.5, PM10	staggered DID	(1) routine and revisit inspections can all reduce AQI, PM2.5, and PM10, and the former has a stronger effect; (2) in the four weeks before the arrival of CEPI, all air quality indexes increase significantly, suggesting the existence of advance action; (3) in the four weeks after the leave of CEPI, air quality continues

					to improve, suggesting no evidence of a rebound effect.
Wang et al. (2021b)	290 cities	the whole period of routine inspection and part period of revisit inspection	AQI, PM2.5, PM10, NO2, SO2, CO, O3	RDD	(1) routine inspection significantly decreases air quality indexes, including AQI, PM2.5, PM10, SO2, and NO2, but has no significant effect on CO and significantly increases O3; (2) revisit inspection significantly decreases all air quality indexes except for O3, and the effect on O3 is positive and significant; (3) the magnitude of pollution reduction in revisit inspection is larger than in routine inspection.
Yuan et al. (2022)	282 cities covered by four batches of routine inspection	January 1, 2016, to December 31, 2018	AQI, PM2.5, PM10, NO2, SO2, CO, O3	event study	(1) implementation of CEPI significantly reduces air quality indexes AQI, PM2.5, PM10, NO2, SO2, and CO, but increases the pollution of O3; (2) AQI and PM10 decrease significantly in 8-14 days before the arrival of CEPI, suggesting the existence of advance action; (3) air quality rebounds immediately in 1-7 days after the CEPI leaves, and air quality is even worse compared to the pre-CEPI periods after four months after the CEPI leaves, suggesting the effect of CEPI is not sustainable in the long-run.
Zheng & Na (2020)	130 cities covered by four batches of routine inspection	January 1, 2016, to December 31, 2017	AQI, PM2.5, PM10, NO2, SO2, CO, O3	staggered DID and RDD	(1) By DID method, implementation of CEPI significantly reduces AQI, PM2.5, PM10, and O3, but has no significant effects on NO2, SO2, and CO; By RDD, all air quality indexes decrease significantly after the implementation of CEPI; (2) AQI begins to deteriorate in 30-60 days after the CEPI leaves, suggesting a rebound effect in the post-CEPI period; (3) effect of the CEPI is significant in the second to fourth batches of inspection but insignificant in the first inspection batch.

3. Data and Empirical Design

3.1 Data

We match daily production-side electricity consumption, air quality, and weather data for counties in Zhejiang and Jiangsu provinces to obtain a unique database for analysis, from January 1, 2019, to June 30, 2022. Considering the COVID-19 outbroken during the period may affect production behaviors (Chen et al., 2022a), we use the cumulative number of confirmed cases as a proxy for production restrictions.

Production-side Electricity Consumption Data. The county-industry-daily level electricity consumption data are provided by State Grid Zhejiang and Jiangsu Electric Power companies. The State Grid is the largest electricity transmission and supply company in China, and its operations cover 26 provinces with a population of over 1.1 billion.[9] To promote digital transformation, the State Grid has developed an online system to collect the electricity consumption information of customers systematically and is gradually expanding it to all covered provinces. Zhejiang and Jiangsu are pioneers in adopting the smart grid system, with stable and complete data collection.[10] The high-frequency electricity consumption data are fine-grained at both spatial and industry levels. The data cover 90 counties (or districts) in 11 prefecture-level cities in Zhejiang, and 52 county units in 13 prefecture-level cities in Jiangsu.[11] Appendix Table A2 presents the detailed sample counties. The data cover all primary, secondary, and tertiary sectors that are classified by the Sectoral Classification System GB/T4754-2011, a total of 18 industries are included in the analysis.[12] For manufacturing, the electricity consumption data of 31 sub-sectors, corresponding to C13-C43 in the GB/T4754-2011, are

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[9] For more detailed information on State Grid, please see: http://www.sgcc.com.cn/html/sgcc_main_en/col2017112307/column_2017112307_1.shtml; The China Southern Power Grid covers the power supply from five provinces not included in the State Grid. These provinces are Guangdong, Guangxi, Yunnan, Guizhou, and Hainan.

[10] The new generation of electricity information collection system has been online and running in six provinces: http://www.chinasmartgrid.com.cn/news/20220113/640963.shtml.

[11] For Jiangsu Province, the electricity consumption data of municipal districts in each city are grouped together. For example, the county unit "municipal district (*shixiaqu* in Chinese)" of Suqian City includes two sub-districts, Sucheng District and Suyu District. This explains why the number of county units in the data is less than the number of counties in the administrative division.

[12] Holz (2013) provides an English cross-reference to the GB/T4754-2011 industry classification. There are 20 industries in the GB/T4754-2011, with classification codes from A to T. In the electricity consumption data, industry P (Education) and R (Culture, sports, and entertainment) are combined into a new industry, "Education, culture, sports, and entertainment". Industry S (Public administration, social insurance, and social organizations) and industry T (International organizations) are combined into another new industry, "Public administration, social organizations, and international organizations". Therefore, our data have two fewer industries than the GB/T4754-2011.

also available. The real-time electricity consumption data are a plausible reflection of production conditions (Sun & Anwar, 2015). Leveraging the high-frequency electricity consumption data, Wang et al. (2021a) find that production rebounded greatly after COVID-19 control measures eased, indicating a post-pandemic industry recovery.

Air Quality Data. To assess the effect of the second round of CEPI on air quality, we collect daily-level air quality data from China National Environmental Monitoring Center[13]. The original data are available at the monitoring station level, and we aggregate it to the county level by using inverse distance weighting (IDW), a standard approach in the literature (Deschênes & Greenstone, 2011; Zhang et al., 2018b), to match the electricity consumption data. We focus on three pollution indicators-AQI, PM2.5, and PM10, because the central government adopts them as key measurements to evaluate pollution control, and local governments have stronger incentives to control PM emissions (Wang et al., 2019; Zheng & Na, 2020).

Weather Data. Seasonal fluctuations in meteorological factors may also affect industry production and electricity consumption. Weather variables, including daily average temperature, precipitation, wind speed, relative humidity, and atmospheric pressure, are obtained from the National Meteorological Information Centre.[14] We aggregate the original weather data to the county-daily level using a method similar to processing the air quality data. By controlling for weather factors in the empirical analysis, electricity consumption reflects industry production conditions more reliably.

COVID-19 Cases Data. The outbreak of the COVID-19 pandemic during the sample period inevitably shocks economic production. On the one hand, measures the government takes to stop the spread of the virus, such as lockdowns, can directly reduce productive activities (Chen et al., 2022). On the other hand, to lower the risk of disease, workers may reduce mobility and be actively away from field production (Qiu et al., 2020). We obtain the statistics of COVID-19 cases at the prefectural-city level from the Sina News.[15] There are two types of case data available: the number of new confirmed cases per day, and the cumulative number of confirmed cases from the start of the outbreak. Since the number of new confirmed cases per day in Zhejiang and Jiangsu during the second round of CEPI is quite sporadic, we control for the cumulative number of confirmed cases in the baseline

[13] The real-time air quality data are available at: https://air.cnemc.cn:18007/.
[14] Weather data are available at: http://www.data.cma.cn/en. However, the National Meteorological Information Centre no longer releases weather data after 2020. Weather data after 2020 can be obtained from the Resource and Environment Science and Data Center upon request: https://www.resdc.cn/data.aspx?DATAID=230.
[15] The data website is: https://news.sina.cn/zt_d/yiqing0121?vt=4.

analysis to mitigate the influence of the pandemic.[16]

Timeline of the second round CEPI in Zhejiang and Jiangsu. The second round of CEPI was implemented much earlier in Zhejiang, from September 1, 2020, to October 1, 2020, partly because the "revisit" phase of the first round of CEPI did not cover Zhejiang. The second round of CEPI stationed in Jiangsu was slightly later, from March 25, 2022, to April 25, 2022. Following Karplus & Wu (2019), we define various periods of the second round of CEPI in terms of weekly scales. We set 7-12 weeks before the arrival of the central inspection team as reference weeks and 1-6 weeks before the arrival as the announcement period. The week of the arrival of the inspection team and the next three weeks is the on-site inspection period. We define the first four weeks after the inspection team leaves, 4-7 weeks after the start of the inspection, as the post-CEPI period to investigate the potential rebound effects in the baseline analysis.

The summary statistics of the main variables are presented in Table 2, divided by CEPI periods. Interestingly, during the announcement period, the electricity consumption increases significantly compared to reference weeks. The 13.8% magnitude increase in production, from 15.535 kWh to 17.675 kWh, suggests an early action by local governments in responding to central inspections. When nearing the arrival of the inspection team and during the on-site inspection period, production activities are reduced to levels below reference weeks. However, after the inspection team left, the production rebounded slightly, especially for the secondary industry, which production even exceeded the pre-inspection level. The pattern presented by the electricity consumption data reveals strategic responses of local governments to CEPI. However, a similar pattern is not found when investigating air quality data. As a placebo test, we move the arrival date of central inspection teams in Zhejiang and Jiangsu advance by one year, and present summary statistics during the pseudo-CEPI periods in Appendix Table A3. We find almost opposite patterns in the placebo test compared to Table 2. Production activities decreased during the pseudo-announcement periods and increased significantly after the pseudo-arrival of the inspectors, which can not be attributed to the rational behaviors of local governments but rather reflects the seasonality of production across industries. Therefore, the pattern in Table 2 mirrors the response effect induced by the implementation of CEPI.

[16] There is an average of 0.0007 new cases in Zhejiang and an average of 0.3166 new cases in Jiangsu during the period of CEPI. See also the descriptive statistics in Table 2. The results are robust when controlling for the number of new confirmed cases each day.

Table 2: Summary statistics by CEPI periods

	Reference weeks	Announcement period	On-site period	Post-CEPI period
	(7-12 weeks before the arrival of central inspectors)	(1-6 weeks before the arrival of central inspectors)	(0-3 weeks after the arrival of central inspectors)	(4-7 weeks after the arrival of central inspectors)
Observations	6,468	6,468	4,312	4,312
Electricity consumption				
Total production electricity consumption: million kWh	15.535 (19.122)	17.675 (29.555)	15.144 (18.060)	15.172 (18.663)
Primary industry consumption: million kWh	0.076 (0.093)	0.087 (0.120)	0.071 (0.104)	0.059 (0.067)
Secondary industry consumption: million kWh	11.515 (14.188)	13.626 (24.750)	12.070 (14.655)	12.267 (15.209)
Tertiary industry consumption: million kWh	3.944 (6.421)	3.961 (6.499)	3.003 (4.725)	2.846 (4.821)
Air quality				
AQI: 1-500	54.452 (33.488)	49.086 (24.535)	50.458 (16.567)	48.556 (13.763)
PM2.5: μg/m^3	30.735 (16.845)	27.876 (14.118)	29.591 (11.980)	26.696 (11.830)
PM10: μg/m^3	51.319 (33.844)	50.880 (32.518)	49.483 (20.804)	48.399 (18.778)
Weather				
Temperature: °C	17.657 (11.427)	21.055 (10.657)	20.306 (5.387)	19.374 (2.884)
Precipitation: mm	6.781 (13.623)	3.589 (11.238)	4.447 (11.635)	1.186 (4.796)
Wind speed: m/s	1.848 (0.691)	2.292 (0.953)	1.919 (0.816)	2.153 (0.817)
Relative humidity: %	81.366 (10.172)	71.507 (12.902)	71.849 (15.157)	69.315 (12.025)
Atmospheric pressure: hPa	1.848 (0.691)	2.292 (0.953)	1.919 (0.816)	2.153 (0.817)
COVID-19 cases				
# of new confirmed cases: people	0.001 (0.037)	0.258 (1.898)	0.204 (0.817)	0.068 (0.563)
# of cumulative confirmed cases: people	126.264 (156.627)	132.256 (156.687)	139.916 (155.544)	144.429 (155.461)

Notes: Table 2 presents the means and standard deviations (in parentheses) of variables during various CEPI periods.

The central inspection team arrived in Zhejiang on September 1, 2020, and in Jiangsu on March 25, 2022. The data from Zhejiang and Jiangsu are pooled together to produce Table 2.

3.2 Empirical Strategy

To identify the causal effects of the second round of CEPI on air quality and production activities during different stages of implementation, we develop a novel approach combing the advantages of one-size-fits-all DID (Fu & Gu, 2017) and event study (Karplus & Wu, 2019) methods.[17] In brief, we follow the phase of CEPI divided by Karplus & Wu (2019) and combine event study design to detect the effect of CEPI during different stages. Moreover, for a specific county unit, we include its observations on the year of CEPI implementation and the one year before CEPI in the analysis, and assign the latter to a control group. By doing so, we construct two-dimensional differences for county units: CEPI period variations within a year, and year-to-year changes. Our empirical specification is:

$$
\begin{aligned}
Y_{cd} = \alpha + & \sum_{d \in j=-1}^{-6} \beta_j \cdot Announce_{cj} \times \mathbf{1}(CEPI_{cy}) + \sum_{d \in j=0}^{3} \gamma_j \cdot On\_site_{cj} \times \mathbf{1}(CEPI_{cy}) \\
& + \sum_{d \in j=4}^{7} \varphi_j \cdot Post_{cj} \times \mathbf{1}(CEPI_{cy}) + \sum_{d \in j=-1}^{-6} \delta_j \cdot Announce_{cj} + \sum_{d \in j=0}^{3} \tau_j \cdot On\_site_{cj} \qquad (1) \\
& + \sum_{d \in j=4}^{7} \mu_j \cdot Post_{cj} + \boldsymbol{X}_{cd}\theta + f(t) + \xi_d + \pi_{county-year} + \psi_{city-month} + \varepsilon_{cd}
\end{aligned}
$$

where Y_{cd} indicates the outcomes of county unit c on date d. When examining the effect of CEPI on air quality, Y_{cd} is represented by the logarithm of AQI, PM2.5, and PM10. To explore the impact of CEPI on production behaviors across industries, Y_{cd} includes the logarithm of total electricity consumption, and the logarithm of primary, secondary, and tertiary sectors' electricity consumption. j is the indicator in the week unit, representing the time away from the arrival of central inspectors. $Announce_{cj}$ is a group of dummy variables representing the announcement period of CEPI. Since the central inspection team arrived in Zhejiang on September 1, 2020, the 36th week in 2020, then if d belongs to the 35th week in 2019 or 2020, $Announce_{c,j=-1}$ equals one for counties in Zhejiang. The

[17] When the central inspection team arrives at a province, all prefectural cities and counties in the province are treated by CEPI. This case is similar to Fu & Gu (2017), which analyzed the effect of the nationwide highway toll waivers during the National Day holiday in 2012 on air pollution. We refer to these cases as "one-size-fits-all" policy interventions.

central inspection team arrived in Jiangsu on March 25, 2022, the 13th week of the year. Therefore $Announce_{c,j=-1}$ equals one for counties in Jiangsu if d belongs to the 12th week in 2021 or 2022. Otherwise, $Announce_{c,j=-1}$ equals zero. $\mathbf{1}(CEPI_{cy})$ is the indicator for the real CEPI policy year, which equals one for counties in Zhejiang in 2020 and one for counties in Jiangsu in 2022. $\mathbf{1}(CEPI_{cy})$ equals zero for counties in Zhejiang in 2019 and one for counties in Jiangsu in 2021. On_site_{cj} is a series of dummy variables indicating the on-site inspection period, zero to three weeks after the arrival of inspectors. $Post_{cj}$ represents the post-CEPI period, weeks within a month after central inspectors leave. Thereby, coefficients of DID terms, β_j, γ_j, and φ_j, capture the policy effects of CEPI during different periods compared to reference weeks, 7-12 weeks before the arrival of inspectors. By adopting the setting of Equation (1), we remove the seasonality of air quality and electricity in the same periods of pseudo and real policy years, which are orthogonal to the implementation of CEPI, to identify the causal effects of CEPI. $\boldsymbol{X}_{cd}$ is a vector of control variables, including weather variables and the cumulative number of confirmed COVID-19 cases listed in Table 2. We include the squared term for temperature in $\boldsymbol{X}_{cd}$ to control for the nonlinear relationship between temperature and electricity consumption (Yao, 2021). We also include the time polynomial $f(t)$ to control time trends around the start of CEPI flexibly (Auffhammer & Kellogg, 2011; Fu & Gu, 2017). We use a fourth-order polynomial in the baseline analysis, and the results are robust for other polynomial orders.[18] ξ_d includes weekend fixed effects and whether date d is a national holiday.[19] We also control for abundant high-dimensional fixed effects to remove spatial and temporal confounders. County-by-year fixed effects $\pi_{county-year}$ flexibly absorb yearly shocks to specific counties, and city-by-month fixed effects $\psi_{city-month}$ further control for month-to-month varying confounders across prefectural cities.

[18] We try polynomial orders from the first order to the fifth order, and the results are very similar. However, higher orders are infeasible since polynomials overfit the outcomes.

[19] Arrangements for national holidays in 2019-2022 are from the website of the State Council:
http://www.gov.cn/zhengce/content/2018-12/06/content_5346276.htm;
http://www.gov.cn/zhengce/content/2019-11/21/content_5454164.htm;
http://www.gov.cn/zhengce/content/2020-11/25/content_5564127.htm;
http://www.gov.cn/zhengce/content/2021-10/25/content_5644835.htm.

Standard errors are clustered at the prefectural-city level.

We also explore the **average** policy effects at different periods of CEPI compared to reference weeks, and thus Equation (1) is modified to:

$$
\begin{aligned}
Y_{cd} = \alpha + \beta \cdot Announce_{cd} \times \mathbf{1}(CEPI_{cy}) + \gamma \cdot On\_site_{cd} \times \mathbf{1}(CEPI_{cy}) \\
+ \varphi \cdot Post_{cd} \times \mathbf{1}(CEPI_{cy}) + \delta \cdot Announce_{cd} + \tau \cdot On\_site_{cd} + \mu \cdot Post_{cd} \\
+ \boldsymbol{X}_{cd}\theta + f(t) + \xi_d + \pi_{county-year} + \psi_{city-month} + \varepsilon_{cd}
\end{aligned} \tag{2}
$$

In Equation (2), the dummy variable $Announce_{cd}$ takes a value of one if date d falls within 1-6 weeks before the arrival of the central inspection team for all sample years. For example, for counties in Zhejiang, if date d belongs to the 30th-35th weeks in 2019 or 2020, then $Announce_{cd}$ equals one. The same logic applies to defining dummy variables On_site_{cd} (0-3 weeks after inspectors arrived) and $Post_{cd}$ (4-7 weeks after inspectors arrived), and $\mathbf{1}(CEPI_{cy})$ is the indicator for the real CEPI policy year. Thus, coefficients β , γ , and φ , capture the **average** policy effects during the announcement, on-site inspection, and post-CEPI periods, respectively. The other settings in Equation (2) are the same as in Equation (1).

4. Empirical Results

4.1 Effects on Air Quality

We first examine the effect of the second round of CEPI, as a repeated game, on county-level air quality. We employ Equation (1) to estimate week-by-week effects and Equation (2) to estimate average effects during different stages of CEPI, and the results are illustrated in Figure 1.[20] In the first three weeks after the CEPI announcement (-6 to -4 weeks), the air quality deteriorates significantly compared to reference weeks, and the pattern is consistent for AQI, PM2.5, and PM10. With the approach of on-site inspection, the AQI gradually improves and reaches a level of indifference with that in reference weeks when the on-site inspection begins. We speculate that the pattern during the announcement period reflects the strategic behavior of local governments after knowing about the arrival of CEPI in advance. They may condone and even encourage highly polluting productions in

[20] We present detailed regression results in Appendix Table A4.

periods far away from the inspection, thereby reducing economic losses in the jurisdiction during the on-site inspection period while having a low risk of being investigated. With weeks nearing the inspection, local governments may shut down or restrict the production of highly polluting industries to reverse air quality urgently. The strategic response results in insignificant average policy effects for all air quality indicators during the announcement period, and our event study design provides a more nuanced detection of advanced actions.

During the on-site inspection period, AQI and PM10 decreased significantly compared to reference weeks, with a 5.5% reduction in AQI and a 6% reduction in PM10. Although the downward trend of PM2.5 is obvious, the estimate of the average effect is insignificant. It is worth noting that the decreasing trend of AQI and PM10 only starts to appear one week after the inspection team arrives, which suggests there may be a one-week lag in changes in particulate matter concentration to production behavior adjustment, and studies use contemporaneous air quality data may misestimate the effect of CEPI. The air quality trend after the inspector leaves is somewhat noisy and does not present a clear pattern. However, we find average effects in the post-inspection period are all significantly negative for all indicators. No week shows a rebound effect with air quality worse than in reference weeks except for the last week in the sample period.

We also split the sample into Jiangsu and Zhejiang for analysis, respectively, and the results are presented in Appendix Figure A1. The air quality patterns in the two provinces are similar, but estimates for Jiangsu are more precise during each stage of the CEPI. One explanation is that since the revisit inspection does not cover Zhejiang in the first round of CEPI, thus the earlier coming second round of CEPI may focus more on its rectification status, which motivates Zhejiang to take substantial measures to improve air conditions and avoids penalization.

Although analysis of air quality changes provides suggestive evidence of the existence of strategic behaviors, we are still unclear on which economic agents dominate the response. In addition, since air pollutants captured by monitors are a combination of human production activities and complex atmospheric processes, air quality changes cannot be directly mapped into the adjustment of production behavior. We caveat the results shown in Figure 1 should be interpreted cautiously. In the next sections, we provide more direct evidence of the effects of CEPI on strategic response behaviors by exploiting high-frequency and industry-specified electricity consumption data.

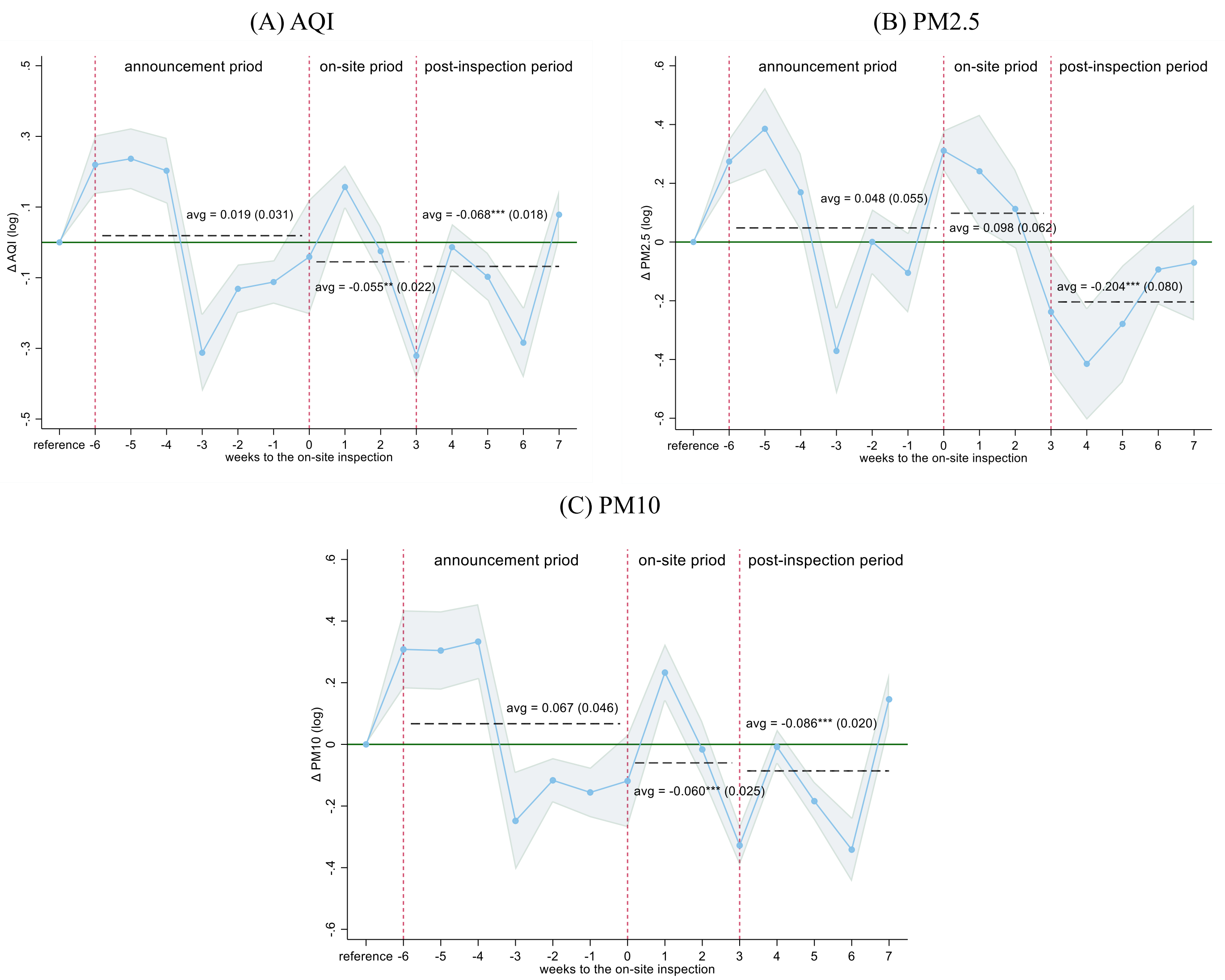


Figure 1: Effects of the second round of CEPI on air quality

Notes: The blue dots represent coefficients for each week compared to reference weeks (7-12 weeks before the arrival of CEPI) estimated by Equation (1). The shaded area represents the 95% confidence interval. Average policy effects during different stages of CEPI are estimated by Equation (2) and represented by black dashed lines. Standard errors clustered at the city level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.2 Effects on Production-side Electricity Consumption

We use high-frequency electricity consumption data across industries as a proxy for production activities. Although some studies have found close associations between electricity consumption and production (Soytas & Sari, 2007; Sun & Anwar, 2015), one may wonder whether the approximation applies to our context. We examine the relationship by employing a variable, nighttime light, to reflect economic development prosperity, which is widely adopted in the literature (Chen & Nordhaus, 2011; Henderson et al., 2012). The monthly-level VIIRS night lights data, from February 2019 to May 2022 in Zhejiang and Jiangsu, is downloaded from NOAA.[21] Gibson et al. (2021) find that VIIRS night lights data have a higher temporal resolution and are more accurate compared to data from other sources. By cropping according to administrative divisions, night lights data are aggregated to the county-month level.[22] Table 3 presents the results of examining the relationship between electricity consumption and night light intensity. Column (1) shows the simple correlation between electricity usage and night light intensity. In column (2), we further control for weather variables simultaneously associated with electricity usage and night lights. In column (3), year, month, and prefectural city fixed effects are additionally controlled. Night light intensity is positively associated with electricity consumption, and coefficients are stable from columns (1) to (3). In column (4), we use the log-log model, and the correlation is still significant, with a 1% increase in electricity usage explaining a 0.25% increase in nighttime light brightness. In summary, we confirm the strong association between electricity usage and the alternative reflection of economic activities- night lights. Our results are consistent with Yao (2021) but with a finer temporal and spatial resolution, which implies electricity consumption is a reliable proxy for production activities.

Table 3: The relationship between electricity consumption and night light intensity

	(1)	(2)	(3)	(4)
		DN value		log(DN value)
Total electricity consumption	0.134***	0.127***	0.116***	
	(0.022)	(0.025)	(0.032)	
log(electricity consumption)				0.254***
				(0.068)
Weather controls	N	Y	Y	Y
Fixed effects	N	N	Y	Y
Observations	181,728	181,728	181,728	181,728
R^2	0.166	0.178	0.414	0.476

Notes: DN value represents the night light intensity, varying from 1 to 63. Weather controls include temperature and its squared, precipitation, wind speed, relative humidity, and air pressure. Fixed effects include year, month, and prefectural city fixed effects. Standard errors in parentheses are clustered at the prefectural city level. *** p<0.01, ** p<0.05, * p<0.1.

We then directly examine the effect of the second round of CEPI on production behaviors. We first focus on the impact on the overall electricity consumption of all industries and illustrate the result

[21] Data are not available for January 2019 and June 2022, and is also not available for Zhoushan City in Zhejiang.

[22] We obtain VIIRS night lights data from the Chinese Research Data Service Platform (CNRDS). CNRDS applies a series of calibrations and pre-processing to the raw data to obtain the data for analysis.
The website is: https://www.cnrds.com/Home/Index#/FinanceDatabase/DB/GNLD/ViewName/VIIRS 中国各县区灯光数据.

in Figure 2.[23] Figure 2 provides more straightforward and clear evidence of the strategic response to CEPI. Before the arrival of inspectors, electricity consumption for production is significantly higher than that in reference weeks and gradually decays with the advance of weeks, and the coefficient of week 0 is no different from zero. During the announcement period, the electricity usage intensity is significantly 7.9% higher than in reference weeks on average, which presents clear evidence for taking advanced action before CEPI to alleviate economic losses. Once the on-site inspection begins, production activities are curtailed immediately to reduce the risk of non-compliance. It is very interesting to find that electricity consumption tends to pick up in the second week after the on-site inspection. At this time, inspection teams have completed the sinking inspection, and plan to leave inspected counties, then organize materials and report upwards. This result reveals a tricky behavior, that is, production rebounds immediately as soon as inspectors leave. Polluting enterprises have the incentive to resume production at this time but maintain a level lower than in reference weeks because inspectors rarely return after leaving, according to the process of CEPI. By combining the average announcement and on-site inspection effect, localities gain a total of 17% net increase in production in these ten weeks,[24] while non-compliance risks are largely reduced through the rearrangement of production. Although the average post-CEPI effect is estimated insignificantly, we find a clear rising trend in electricity consumption after the end of the inspection. The coefficient of week 7 is estimated as significantly positive, suggesting that production reaches the level above reference weeks one month after the CEPI ends.

Moreover, by comparing the patterns presented in Figure 1 and Figure 2, we find that the response of air quality to environmental inspection cannot be fully explained by production adjustments. The changing pattern of air quality is slightly noisy, but changes in electricity consumption provide a direct investigation of strategic behavior. Once again, we confirm the existence of a one-week lag in air quality changes during the on-site inspection period. These findings imply that using air quality indicators as outcomes cannot fully reflect strategic responses.

We reproduce the analysis for Zhejiang and Jiangsu, respectively, and the results are shown in Appendix Figure A2. We find the pattern of Jiangsu is more consistent with that in Figure 2, and the

[23] For the detailed regression result, please see Appendix Table A4.

[24] 0.079*6+(-0.076*4)=17%; The result is close to the sum of coefficients from week -6 to week 3 in Appendix Table A4, which results in 22.7%.

announcement effect and on-site inspection effect are more pronounced for Jiangsu, from both the magnitude and significance of coefficients. Although Zhejiang does not present an advanced overproduction, it suppresses production slightly during the on-site inspection and shares the same rebound trend with Jiangsu. These findings indicate that even though the central government has declared the central inspection will be regular after the first round of CEPI,[25] local governments still have the incentive to perform strategic behavior to cope with the several-years-interval repeated game. When the interval is shorter,[26] the central inspection can force localities to rectify the environmental problems essentially. The result is similar to the intermittent monitoring of air pollution in the US found by Zou (2021).

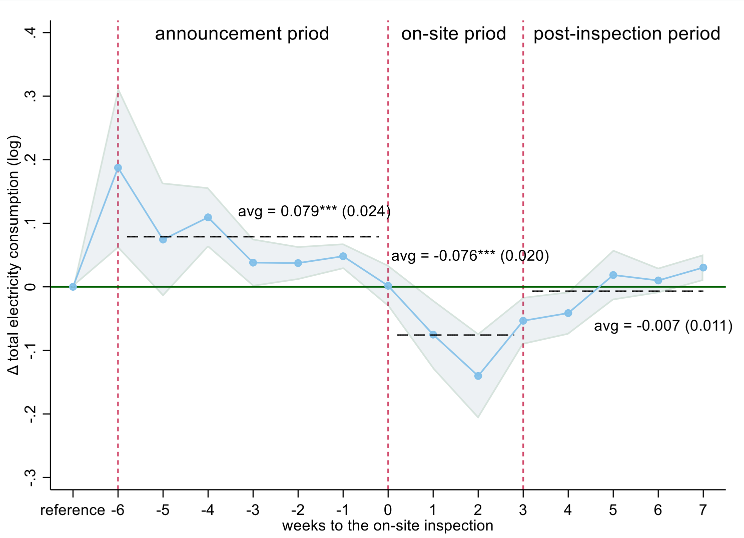


Figure 2: CEPI effects on total electricity consumption

Notes: The blue dots represent coefficients for each week compared to reference weeks (7-12 weeks before the arrival of CEPI) estimated by Equation (1). The shaded area represents the 95% confidence interval. Average policy effects during different stages of CEPI are estimated by Equation (2) and represented by black dashed lines. Standard errors clustered at the city level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We apply a series of attempts to check the robustness of baseline findings, and results are reported in Appendix Table A5. We first change the order of the time trend polynomial $f(t)$, from the first order to the fifth order. As shown in columns (2)-(5) of Appendix Table A5, the choice of polynomial orders does not shake results, and estimates of policy effects during different CEPI stages are stable

[25] 'Environmental Protection Inspector Program (Trial)' was upgraded to 'Central Ecological Environmental Protection Inspector Work Regulations' in June 2019, after the revisit inspection of the first round of CEPI. And also see the news report for more details: https://www.sohu.com/a/227126971_696793.

[26] There is a three-year interval between the revisit inspection of the first round of CEPI and the second round of CEPI in Zhejiang, and there is a five-and-a-half-year interval between the routine inspection of the first round of CEPI and the second round of CEPI in Jiangsu.

compared to baseline results. Second, since we have strictly controlled for county-by-year and city-by-month fixed effects in Equation (1), one may wonder if the model is overfitted by these fixed effects, given the R squared of column (1) of Appendix Table A5 is close to one. We relax the setting of fixed effects and modify the interactive fixed effects to county, month, and year fixed effects. As shown in column (6) of Appendix Table A5, the R squared is almost unchanged, indicating that variations of electricity consumption are well predicted by time-invariant county characteristics, and by monthly and annual patterns. Moreover, average policy effects change less in magnitude, implying baseline results are robust under various fixed effects settings. At last, we change the measurement of COVID-19 from the number of cumulative confirmed cases to the number of new confirmed cases. Column (7) of Appendix Table A5 indicates that the results are still robust.

4.3 Sub-sectors Heterogeneity

Since contributions of environmental pollution and economic losses due to production restrictions differ in sectors, response strategies may vary when faced with the inspection. To explore the industry heterogeneity of the CEPI effects, we first decompose the total electricity consumption into three industrial consumptions and display how electricity usage responds to the inspection across industries in Figure 3.[27] We find that patterns of strategic response present dramatic differences across industries. For the primary industry, there is no evidence of overproduction in advance during the announcement period. On the contrary, electricity usage for agricultural activities decreases continuously after knowing the coming of CEPI, with a magnitude of 4.7% on average. The CEPI is a systematic inspection that targets all aspects of environmental issues, covering not only air pollution, but also water and soil pollution. The non-point source pollution, mainly caused by agricultural activities, leads to soil and water quality deterioration, while treatment of that is a complex and time-consuming process. Local governments may reduce agricultural production before the arrival of the inspector to obtain better soil and water quality, resulting in the pattern presented in Panel (A) of Figure 3. When the on-site inspection starts, agricultural electricity consumption declines more sharply. Panel (B) of Figure 3 shows that the secondary industry, which is more flexible and less costly in production

[27] The classification of three industries is based on the " Regulations on Industrial Classification " issued by the National Bureau of Statistics, which is compatible with Sectoral Classification System GB/T4754-2011.
See: http://www.stats.gov.cn/sj/tjbz/gjtjbz/202302/t20230213_1902749.html. This classification is adopted by electricity consumption accounting. Detailed regression results are presented in Appendix Table A4.

adjustments, obviously exhibits overproductions in advance. The response pattern of the secondary industry is very close to the pattern of overall industries in Figure 2, indicating the announcement effect in Figure 2 is dominated by industrial sectors. The pattern of the tertiary industry is close to the primary industry but slightly differs in magnitude. Moreover, production in all three industries uniformly rises from the second week after the on-site inspection starts. Production revival is the strongest in the secondary industry, with electricity usage from the second week in the post-inspection period (week 5) has significantly exceeded the reference level.

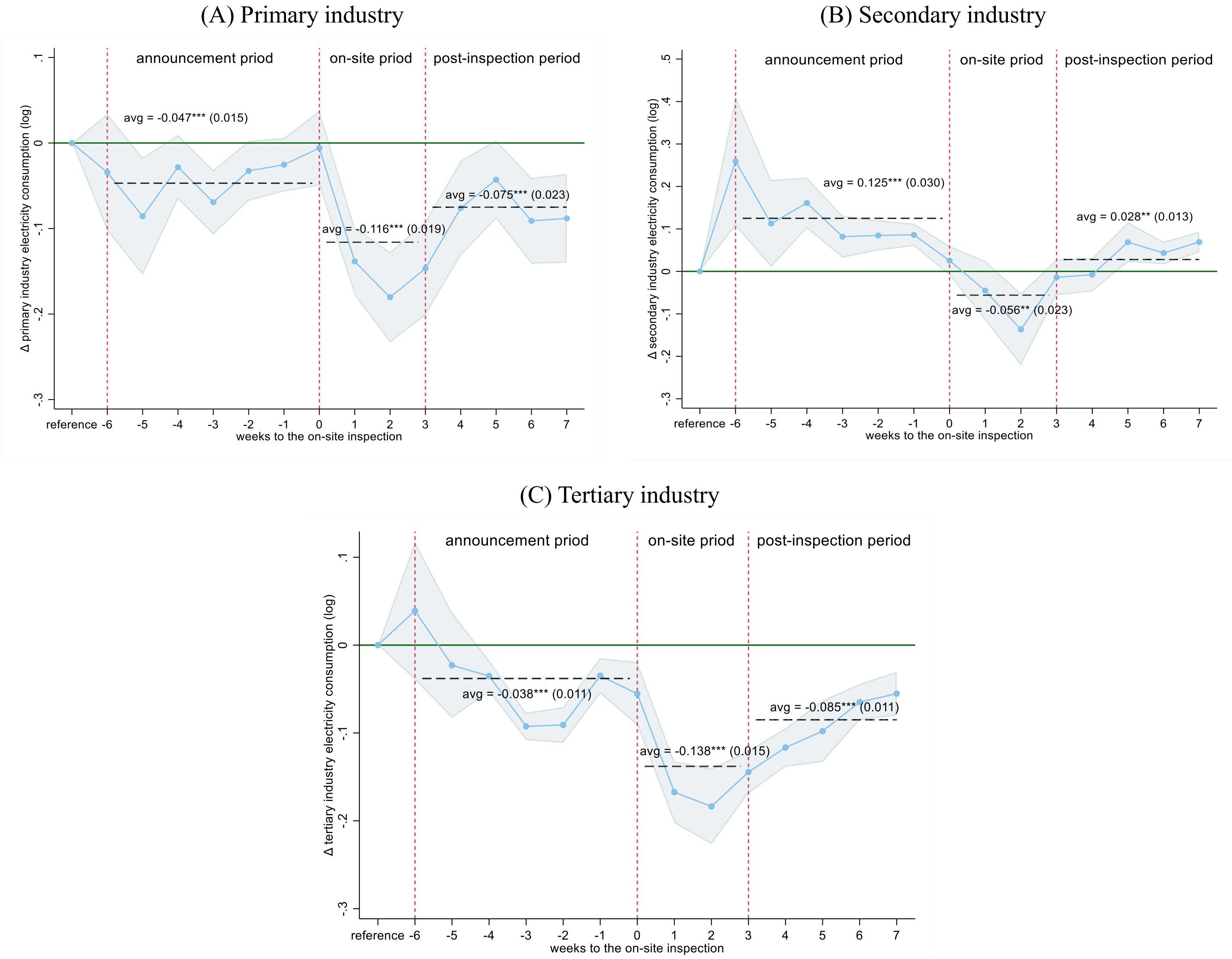


Figure 3: CEPI effects on electricity consumption across industries

Notes: The blue dots represent coefficients for each week compared to reference weeks (7-12 weeks before the arrival of CEPI) estimated by Equation (1). The shaded area represents the 95% confidence interval. Average policy effects during different stages of CEPI are estimated by Equation (2) and represented by black dashed lines. Standard errors clustered at the city level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

We further divide the tertiary industry into producer and consumer service sectors based on classification by the National Bureau of Statistics to extend the analysis.[28] The producer service industry includes sectors that provide support activities for agricultural and industrial productions, thereby can be affected by primary and secondary industries through the value chain. And the consumer service industry refers to service activities that fulfill the final consumption demand of residents. In Appendix Table A6, we provide a detailed list of sub-sectors grouped into the producer and consumer service industries, respectively. As shown in Panel (A) of Figure 4, the response pattern of productive services appears similar to the combination of primary and secondary industries due to its linkage to production activities. There is a very slight sign of overproduction after the announcement of CEPI, with coefficients of week -6 and week -4 estimated as positive and statistically significant at the 10% level. The response pattern of the tertiary industry is highly close to that of the consumer service sector both in magnitude and precision, as shown in Panel (B) of Figure 4. The announcement effect, with an average 5.2% reduction in electricity usage, possibly reflects the temporary efforts of local governments to combat urban pollution, such as managing the operation order of catering and disposing of domestic garbages properly.[29]

(A) Producer service industry

(B) Consumer service industry

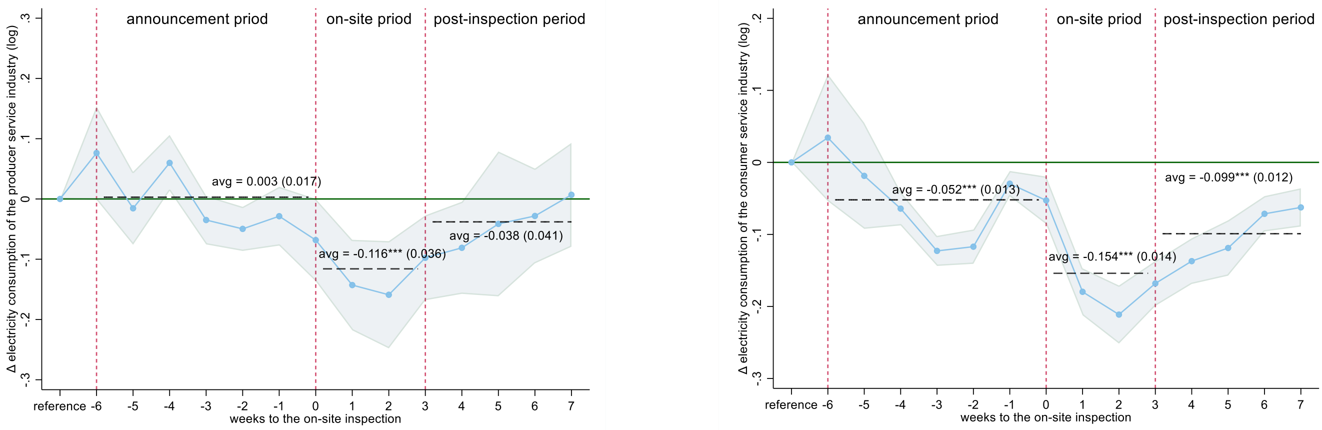


Figure 4: CEPI Effects on electricity consumption of producer/consumer service industry

Notes: The blue dots represent coefficients for each week compared to reference weeks (7-12 weeks before the arrival of CEPI) estimated by Equation (1). The shaded area represents the 95% confidence interval. Average policy effects during different stages of CEPI are estimated by Equation (2) and represented by black dashed lines. Standard errors clustered at the city level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

[28] We follow the classification in "Statistical Classification of Producer/Consumer Service Industry (2015)", which is based on the Sectoral Classification System GB/T4754-2011.
See http://www.stats.gov.cn/sj/tjbz/gjtjbz/202302/t20230213_1902758.html for the classification of the producer service industry, and see http://www.stats.gov.cn/xxgk/tjbz/gjtjbz/201904/t20190418_1758935.html for the classification of the consumer service industry.

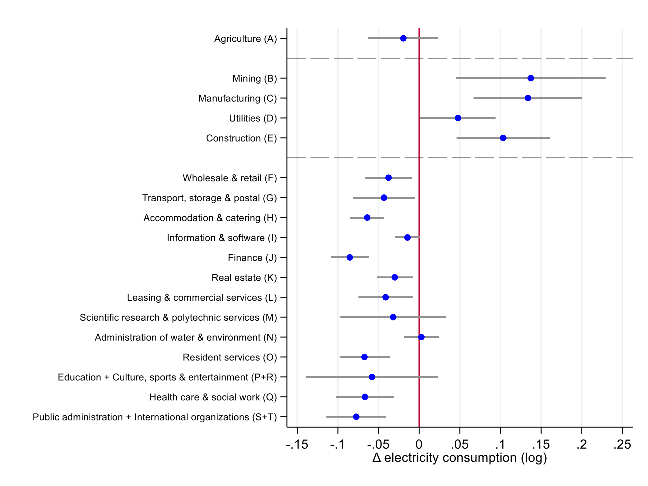
[29] One example is that the Urban Administration and Regulation of Jinan holds a deployment meeting six weeks before the arrival of the central inspection team. See the report at: http://jnzf.jinan.gov.cn/art/2021/7/5/art_12954_4761642.html.

Benefiting from the fine sectoral resolution of the electricity consumption data, we can deeper explore the sectoral heterogeneity of strategic behaviors. According to the classification GB/T4754-2011, economic industries in China are divided into 20 classes. We list the industry classification in the electricity consumption data in Appendix Table A7, which is consistent with GB/T4754-2011. The results of industry heterogeneity are plotted in Figure 5. To investigate the response of industries during the on-site inspection and post-inspection periods more obviously, we assign the phase prior to the target stage as the reference period. Therefore, in Panel (A) of Figure 5, the reference period is 7-12 weeks before the arrival of CEPI. In Panel (B) of Figure 5, the reference period is the announcement period, -6 to -1 weeks before the on-site inspection. And Panel (C) of Figure 5 shows the rebound effects during the post-CEPI period. We also uniformly set the reference period for each stage as 7-12 weeks before the on-site inspection and plot policy effects in Appendix Figure A3.

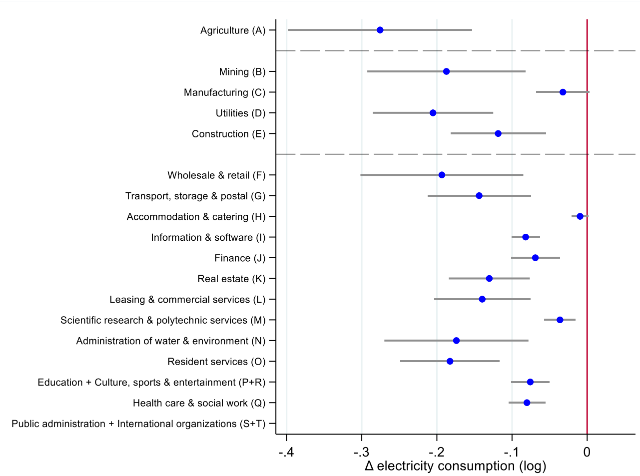
Figure 5 demonstrates that strategic behaviors vary dramatically across industries. Although advanced actions are prevalent in all industries, overproduction is concentrated in the industrial sector. The announcement effects are estimated as positive and statistically significant for all four industries of the secondary industry, with the average effects of Mining (B) and Manufacturing (C) being close to 15%. Consistent with findings in Figures 3 and Figure 4, electricity usage in service industry sectors mainly experiences a decrease before the arrival of inspectors, while the effect is insignificant for the agriculture sector.[30] During the strict on-site inspection period, production activities of all sectors decrease significantly to avoid non-compliance and penalties, and Panel (B) of Appendix Figure A3 confirms that no sectors produce with an intensity above the level in 7-12 weeks before CEPI. Once the inspector leaves, production activities of all sectors rebound rapidly to compensate for losses during the inspection. This finding is not noticeable in Panel (C) of Appendix Figure A3 but is clearly detected in Panel (C) of Figure 5. The mining industry has the largest magnitude of rebound, and retaliatory productions of Manufacturing (C) and Utilities (D) in the secondary industry even cause electricity usage above the level in the pre-announcement period. In summary, the industrial sector has the strongest extent of strategic response in coping with CEPI, which implies the inspection is limited in essentially improving localities' industrial pollution.

[30] Agriculture (A) includes five sub-sectors, Farming (A1), Forestry (A2), Animal husbandry (A3), Fisheries (A4), and Agricultural services (A5). Agricultural services (A5) is classified in the tertiary sector, which causes the pattern in Panel (A) of Figure 5 to differ slightly from that in Figure 3.

(A) Announcement effects



(B) On-site inspection effects



(C) Post-inspection effects

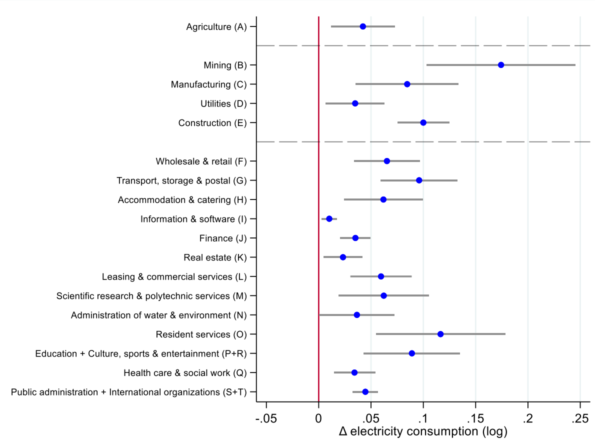
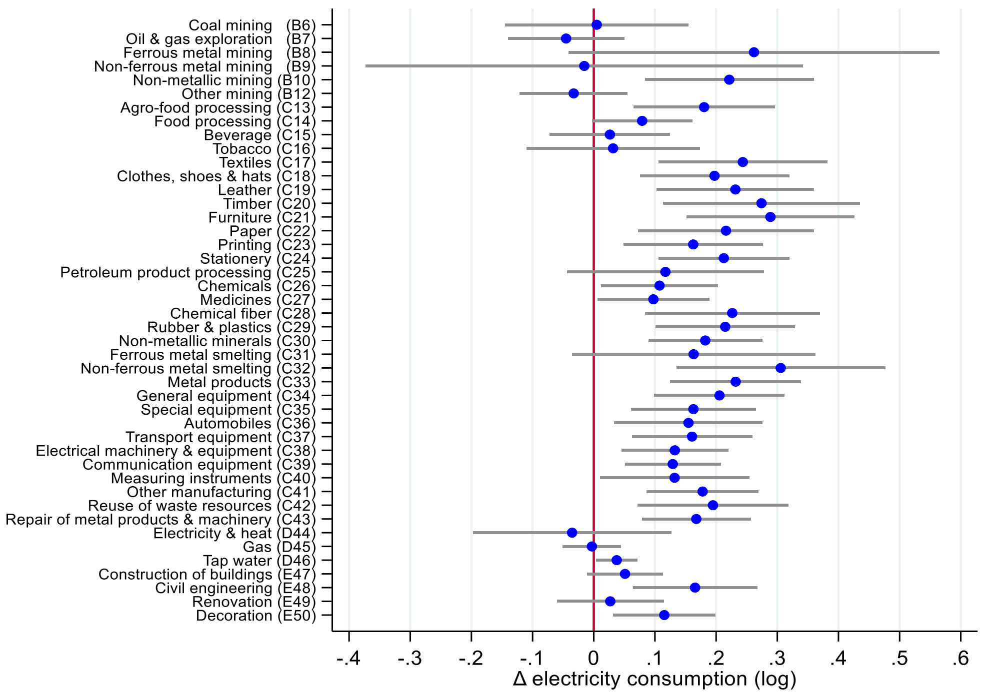


Figure 5: Industry heterogeneity of CEPI effects

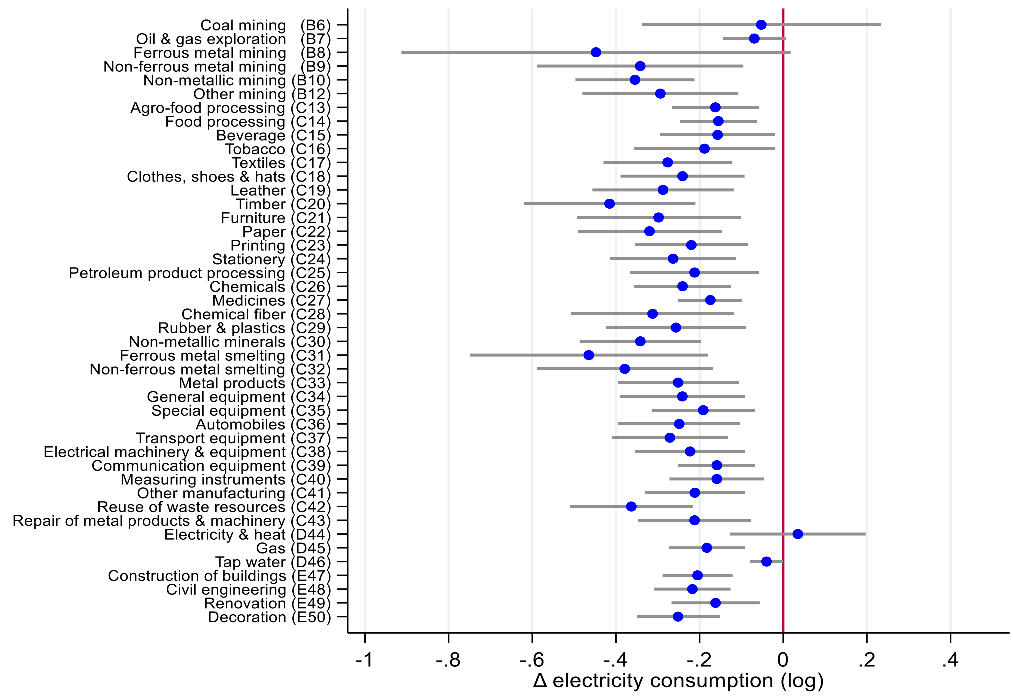
Notes: The blue dots represent point estimates of average policy effects in each industry following Equation (2). The solid gray lines represent the 95% confidence interval. In Panel (A), the reference period is 7-12 weeks before the arrival of CEPI. In Panel (B), the reference period is the announcement period. In Panel (C), the reference period is the on-site inspection period. Industry codes are presented in parentheses, which are consistent with the classification of GB/T4754-2011. Standard errors are clustered at the city level.

Since the secondary industry is the major contributor to the strategic response observed for the overall national economy, we further exploit the electricity usage data of sub-sectors in Mining (B), Manufacturing (C), Utilities (D), and Construction (E) to explore the response heterogeneity. Sub-sectors classified into the four industries by GB/T4754-2011 are presented in Appendix Table A8, and the results of sub-sector heterogeneity are plotted in Figure 6. The policy effects in different stages of sub-sectors within the secondary industry coincide with patterns presented in Figure 5. However, not all sub-sectors achieve overproduction during the announcement period. The announcement effects are more pronounced from both magnitude and precision for light industrial sectors, from Textiles (C17) to Stationery (C24). Coefficients of some heavy industrial sectors in Panel (A) of Figure 6, such as Coal mining (B6) to Non-ferrous metal mining (B9), and Petroleum product processing (C25), are estimated as insignificant. This finding implies that even though these heavy industrial sectors have the incentive to take advanced actions after knowing the soon-coming inspection, the inflexibility of the production process constrains their achievement of overproduction. During the on-site inspection period, almost all industrial sectors reduce their production significantly compared to the announcement period, indicating the kind of one-size-fits-all production restrictions or shutdowns governance is homogeneous across sectors. After the inspector leaves, rebound patterns across sectors are closer to their announcement effects.

(A) Announcement effects



(B) On-site inspection effects



(C) Post-inspection effects

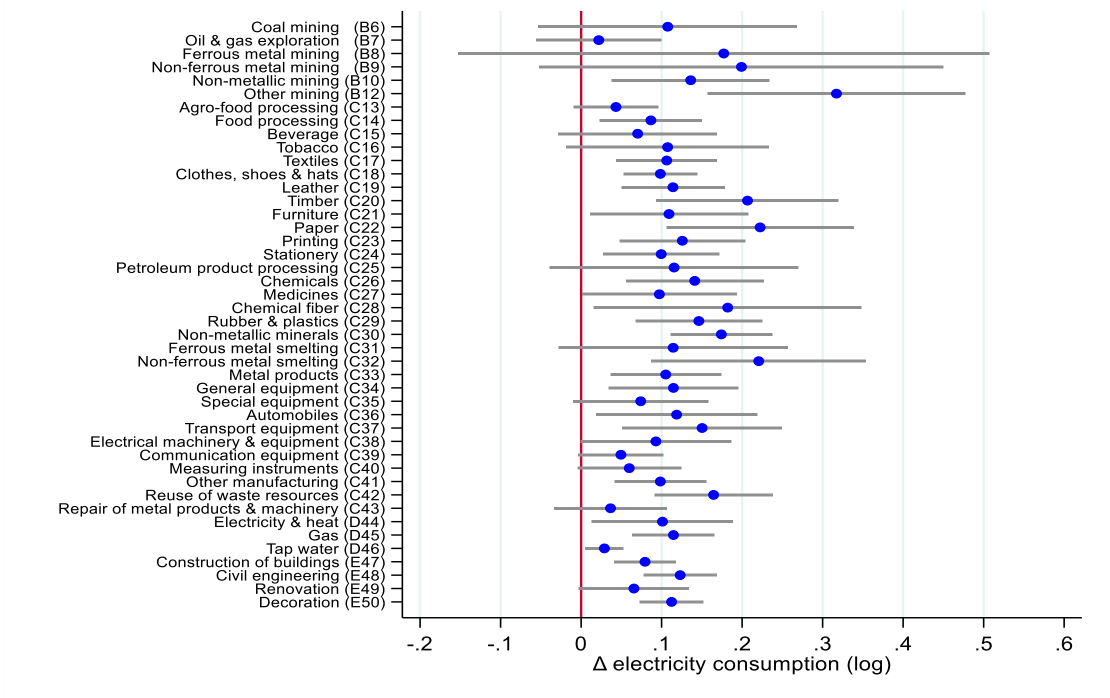


Figure 6: Response heterogeneity of sub-sectors in the secondary industry

Notes: The blue dots represent point estimates of average policy effects in each industry following Equation (2). The solid gray lines represent the 95% confidence interval. In Panel (A), the reference period is 7-12 weeks before the arrival of CEPI. In Panel (B), the reference period is the announcement period. In Panel (C), the reference period is the on-site inspection period. Sub-sector codes are presented in parentheses, which are consistent with the classification of GB/T4754-2011. Standard errors are clustered at the city level.

4.4 Mechanisms: Political Economy Perspective

Until now, we are unclear on what economic agents lead strategic response behaviors observed above. We infer that micro-level enterprises are not the single subject that causes the response pattern for the following reasons. First, in the environmental regulatory system of China, the major inspection target has changed from enterprises to governments after 2014. Although polluting enterprises caught during the CEPI also suffer fines, it is hard to imagine that sectors in all industries reduce their production during the on-site inspection period, as only half of the cities in a province are covered by the sinking inspection. Second, the central government usually conveys the coming of CEPI only to the provincial government to facilitate the preparation for receptions by the provincial government. Although the information is cascaded from the provincial government to the prefectural and county governments, it is unlikely that the industrial sectors systematically overproduce before the arrival of inspectors, as shown in Panel (A) of Figure 6, with the absence of information leakage from local governments. In fact, both previous studies (such as Karplus & Wu, 2019; Yuan et al., 2022) and real-world experience suggest that the local government relies on authority or collusion with enterprises to achieve short-term environmental improvements to cope with CEPI.[31] In this section, we explore the collaborative role of governments in causing strategic responses from political economy perspectives.

We start with incentives for local governments to collude with enterprises. The secretary and mayor of a prefectural city are the head of the party committee and government, respectively.[32] They are responsible for environmental problems in their jurisdictions, and their characteristics may moderate the strength of strategic responses. We collect information on secretaries and mayors of prefectural cities in Zhejiang and Jiangsu who were in office during the second round of CEPI from official websites. The information includes the officials' names, gender, birth date, and when beginning office as secretary or mayor. Male officials dominate the constitution of high-level leaders, and only four of the 48 secretaries or mayors in 24 cities are female. The average age of secretaries is 54.61, and the average age of mayors is 52.65. When CEPI begins, officials in the two provinces have served as secretaries for 17.84 months and as mayors for 17.33 months on average.

[31] The MEE has expected that some local governments may restrict or shut down production to cope with the inspection and has issued a statement strictly prohibiting the one-size-fits-all behavior;
For the report, please see: http://www.gov.cn/hudong/2018-05/29/content_5294357.htm.
[32] Not finished, collect information on county officials for the next step analysis.

We exploit two key points to examine the role of leaders' motivation in causing strategic behavior. The first is the time away from the retirement of secretaries and mayors at the start of CEPI. According to the Civil Servant Law,[33] officials should retire when they reach the retirement age set by the state, and the retirement age of civil servants is 55 for females and 60 for males in China. The closer to retirement, the more cautious officials are about political dereliction of duty because it is strongly related to the treatment they enjoy after retirement, including political, living, medical, and other treatments. The second is the probability of being further promoted, which is proxied by the time an official has been in office as secretary or mayor. When an official stays in a post for a longer time, the possibility of promotion is expected as higher, and therefore the official may be more careful about responding to the central inspection. We generate two variables, months away from the retirement of the official and months the official has served as secretary or mayor, and then interact the two variables with dummies $CEPI\_stage_{cd} \times \mathbf{1}(CEPI_{cy})$ in Equation (2).[34] Results are presented in Table 4. To highlight the effect of officials' motivation on strategic responses during different stages of CEPI, we assign the period before each stage as the reference period. Coefficients listed in green, red, and blue boxes in Table 4 indicate moderate effects of officials' characteristics on production-side electricity consumption during the announcement, on-site inspection, and post-inspection stages, respectively.

Panel A of Table 4 demonstrates how the time to retirement affects CEPI effects in different stages. The estimates are close in magnitude for the secretary and mayor. Columns (1) and (3) of Panel A imply overproduction during the announcement period is significantly depressed when the arrival of CEPI is nearer to the retirement time of leaders. However, the moderate effects are no longer apparent after the start of the on-site inspection. Panel B of Table 4 presents how the possibility of leaders being promoted affects the strategic responses. When the secretary or mayor is more likely to be promoted (has been in office for longer months), the overproduction in the announcement period reduces significantly, and there are also fewer production restrictions or shutdowns during the on-site inspection period. However, considering triple difference terms are only marginally significant for rebounds in the post-inspection period, the betterment of strategic responses in preceding periods is only temporary, and environmental qualities are not substantially improved after inspectors leave.

[33] The official website for Civil Servant Law of the PRC is: http://www.gov.cn/guowuyuan/2018-12/30/content_5353490.htm.
[34] The group of dummy variables $CEPI\_stage_{cd}$ include $Reference_{cd}$, $Announce_{cd}$, On_site_{cd}, and $Post_{cd}$.

Table 4: Moderate effects of time to retirement and time has been in office

Explained variable: log (total electricity consumption)	*Panel A: Months to retirement*					
	Party secretary			*Mayor*		
	(1)	(2)	(3)	(4)	(5)	(6)
Months_to_retire×*Announce*×**1**(CEPI)	0.0011*		0.0012	0.0014**		0.0012
	(0.0007)		(0.0008)	(0.0006)		(0.0008)
Months_to_retire×*On_site*×**1**(CEPI)	-0.0001	-0.0012		0.0002	-0.0012	
	(0.0003)	(0.0008)		(0.0004)	(0.0008)	
Months_to_retire×*Post*×**1**(CEPI)	-0.0002	-0.0013**	-0.0001	0.0002	-0.0011*	0.0001
	(0.0003)	(0.0005)	(0.0004)	(0.0003)	(0.0006)	(0.0004)
Months_to_retire×*Reference*×**1**(CEPI)		-0.0011*	0.0001		-0.0014**	-0.0002
		(0.0007)	(0.0003)		(0.0006)	(0.0004)
Announce×**1**(CEPI)	-0.0069	-0.0069	-0.0069	-0.0311	-0.0311	-0.0311
	(0.0468)	(0.0468)	(0.0468)	(0.0448)	(0.0448)	(0.0448)
On_site×**1**(CEPI)	-0.0679*	-0.0679*	-0.0679*	-0.0890*	-0.0890*	-0.0890*
	(0.0335)	(0.0335)	(0.0335)	(0.0482)	(0.0482)	(0.0482)
Post×**1**(CEPI)	0.0087	0.0087	0.0087	-0.0237	-0.0237	-0.0237
	(0.0215)	(0.0215)	(0.0215)	(0.0246)	(0.0246)	(0.0246)
Controls & FEs	Y	Y	Y	Y	Y	Y
R^2	0.9894	0.9894	0.9894	0.9894	0.9894	0.9894
Explained variable: log (total electricity consumption)	*Panel B: Months after in-office*					
	Party secretary			*Mayor*		
	(7)	(8)	(9)	(10)	(11)	(12)
Months_after_in-office×*Announce*×**1**(CEPI)	-0.0071***		-0.0086***	-0.0061***		-0.0074***
	(0.0017)		(0.0026)	(0.0015)		(0.0020)
Months_after_in-office×*On_site*×**1**(CEPI)	0.0015	0.0086***		0.0012	0.0074***	
	(0.0016)	(0.0026)		(0.0010)	(0.0020)	
Months_after_in-office×*Post*×**1**(CEPI)	-0.0008	0.0063***	-0.0023	-0.0008	0.0054***	-0.0020*
	(0.0011)	(0.0018)	(0.0014)	(0.0007)	(0.0013)	(0.0010)

Months_after_in-office×*Reference*×**1**(CEPI)		0.0071***	-0.0015		0.0061***	-0.0012
		(0.0017)	(0.0016)		(0.0015)	(0.0010)
Announce×**1**(CEPI)	0.2103***	0.2103***	0.2103***	0.1960***	0.1960***	0.1960***
	(0.0493)	(0.0493)	(0.0493)	(0.0455)	(0.0455)	(0.0455)
On_site×**1**(CEPI)	-0.1028**	-0.1028**	-0.1028**	-0.0981***	-0.0981***	-0.0981***
	(0.0399)	(0.0399)	(0.0399)	(0.0321)	(0.0321)	(0.0321)
Post×**1**(CEPI)	0.0094	0.0094	0.0094	0.0088	0.0088	0.0088
	(0.0258)	(0.0258)	(0.0258)	(0.0213)	(0.0213)	(0.0213)
Controls & FEs	Y	Y	Y	Y	Y	Y
R^2	0.9895	0.9895	0.9895	0.9895	0.9895	0.9895

Notes: Observations are 43,120 for all regressions. *Reference* indicates whether the day falls 7-12 weeks before the CEPI timing in the real CEPI year and the year before the real CEPI year. *Announce* indicates whether the day falls 1-6 weeks before the CEPI timing in the real CEPI year and the year before the real CEPI year. *On_site* indicates whether the day falls 0-3 weeks after the CEPI timing in the real CEPI year and the year before the real CEPI year. *Post* indicates whether the day falls 4-7 weeks after the CEPI timing in the real CEPI year and the year before the real CEPI year. **1**(CEPI) indicates whether the year is the real CEPI year. *Announce*, *On_site*, and *Post* are included as control variables. Control variables include weather controls and the cumulative number of confirmed COVID-19 cases. Time trend is a fourth-order time polynomial. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

We then explore how local governments' capacity to collude with enterprises contributes to strategic response behaviors. The capacity for collusion determines the extent to which enterprises comply with formal or informal arrangements of local governments, which is critical to realizing systemically industry-wide production adjustments. As pointed out by Xi Jinping on March 4, 2016, a healthy government-business relationship consists of two aspects, closeness (also cordialness) and cleanliness.[35] The closeness refers to the fact that governments should care for the development of enterprises and actively provide help for their difficulties. In contrast, cleanliness requires that governments not use their authority for personal gain and engage in private deals with enterprises. We examine how the two components of the government-business relationship moderate the production response to CEPI using the China City Political and Business Relations Ranking 2020 developed by Nie et al. (2020).[36] This data comprehensively assess relationships between prefectural governments and enterprises in China, which use public, survey, and web data to construct indexes. This data contain three major indexes: overall government-business relationship index, closeness index, and cleanliness index, and data for sub-indexes are also available. These indexes range from 1 to 100, with higher scores representing a better government-business environment. The report was released in 2020, but the year used to construct indexes is 2019, which is well-suited for our analysis. Since the data is constructed one year before the second round of CEPI in Jiangsu, and thus rules out noisy changes in the government-business relationship introduced by the inspection.

Similar to that in Table 4, we construct interactions between the total/ closeness/ cleanliness index with $CEPI\_stage_{cd} \times \mathbf{1}(CEPI_{cy})$, and estimates for these triple difference terms are plotted in Figure 7. The result indicates that a better government-business relationship at the prefecture-level help mitigates the extent of strategic responses at all stages of CEPI, as less overproduction during the announcement period, fewer production restrictions during the on-site period, and fewer rebounds after the leave of CEPI. However, estimates are significant only for the cleanliness index, and estimates for the closeness index are small in magnitude and insignificant, which suggests only the cleanliness aspect of the government-business relationship plays a role in moderating strategic responses.

[35] For the report, see: http://theory.people.com.cn/n1/2017/0608/c40531-29327560.html.
[36] The data is available for download at: http://www.niehuihua.com/a/chuban/557.html.

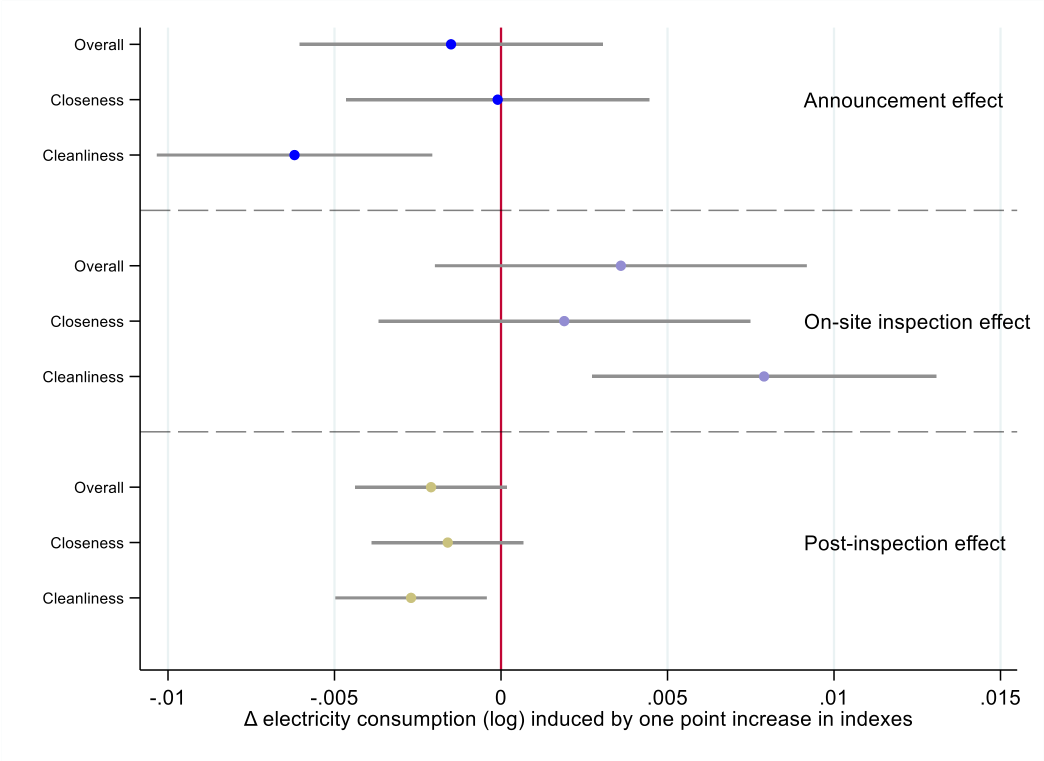


Figure 7: Moderating effects of government-business relationship indexes

Notes: The dots represent point estimates of moderating effects of the overall/ closeness/ cleanliness index. The solid gray lines represent the 95% confidence interval. The reference period for the announcement effect is 7-12 weeks before the arrival of CEPI. The reference period for the on-site inspection effect is the announcement period. The reference period for the post-inspection effect is the on-site inspection period. Standard errors are clustered at the city level.

We reconfirm the importance of the capacity of local governments to mobilize enterprises by performing a similar analysis as in Figure 7 but using sub-indexes as moderators. As shown in Appendix Table A9, the coefficients of all closeness sub-indexes are statistically insignificant. The more opaque the local government, the stronger the intensity of overproduction before on-site inspection and production constraints during the on-site inspection. The lower integrity of the government also contributes to a stronger rebound after the inspector leaves. These findings imply that the corruption-free assistance of the local government to business production does not help enterprises comply with arrangements of uniform production adjustment by the government to cope with political mandates. In contrast, the lower integrity and transparency of the local governments, the higher willingness of enterprises to cooperate with governments' arrangements, which leads to strategic responses.

In summary, our analysis highlights the role of local governments in coordinating strategic production adjustments, where both the incentive and capacity of the government to collude with enterprises are essential determinants. While an integrity government may help improve business efficiency, it makes enterprises lack obedience to the authority of local governments.

5. Conclusion

To fight against pollution, the Chinese government has innovatively developed the central environmental protection inspection system. After finishing the first round of CEPI, the central government has announced that the inspection is to regularized. This paper uses high-frequency production-side electricity consumption data to answer whether CEPI can solve the principal-agent problem under repeated games. Will localities substantially improve pollution under strict inspection or just strategic responses?

By using the empirical design that combines one-size-fits-all DID with the event study approach, this paper finds that during the announcement period, local production activities increase dramatically and decrease immediately once the inspection team arrives. By strategically adjusting production, localities not only mitigate economic losses due to inspection but also reduce the environmental non-compliance risk. When the inspector leaves, production rebounds significantly. These results imply that the effect of CEPI may be a short-term coping with political mandates, like Olympic blue (Chen et al., 2013) and the APEC blue (Wang et al., 2016), and cannot fundamentally address local environmental problems in the long term.

We propose some policy implications that may help to improve the effectiveness of CEPI. First, the CEPI should be implemented more frequently and randomly. We find that Zhejiang, which has a shorter interval between the rounds of inspection compared to Jiangsu, presents a weaker strategic response. This finding implies that more frequent inspections could force substantial local environmental rectification. Moreover, when the inspection becomes more random, localities lack time to make strategic production adjustments and thus can help inspection to identify deep environmental problems.

Second, the central government should strengthen the assessment of local government leaders in normal times and promote the transformation of local governments to a close and clean government-business relationship. We find that local governments with lower cleanliness are more strategic responses. The transformation of the government-business relationship not only helps to cut off strategic responses but also helps local enterprises to improve their productivity.

Third, provincial inspection should be carried out in cooperation with the central inspection. The inspection executed by the provincial government could be more frequent and irregular, thus promoting rectifying environmental problems in prefectural cities or counties.

At last, the central can use technology to solve the principal-agent problem (Greenstone et al., 2022). For example, the central government can install real-time monitoring devices for highly polluting enterprises and collect pollution data to be managed under the MEE directly. With the relaxation of budgets, more polluters can be included in the central monitoring system.

However, there are still limitations of the paper. First, due to the availability of electricity consumption data, we now cover two provinces and cannot assess the overall effect of the second round of CEPI. Second, our heterogeneity analysis is industry or sub-sector specific. Since we cannot identify specific firms in the industry data, we cannot answer how individual firms respond to the CEPI. These questions are still open for future research.

References

Auffhammer, M., & Kellogg, R. (2011). Clearing the air? The effects of gasoline content regulation on air quality. *American Economic Review*, 101(6), 2687-2722.

Athey, S., & Imbens, G. W. (2022). Design-based analysis in difference-in-differences settings with staggered adoption. *Journal of Econometrics*, 226(1), 62-79.

Chen, X., & Nordhaus, W. D. (2011). Using luminosity data as a proxy for economic statistics. *Proceedings of the National Academy of Sciences*, 108(21), 8589-8594.

Chen, Y., Jin, G. Z., Kumar, N., & Shi, G. (2013). The promise of Beijing: Evaluating the impact of the 2008 Olympic Games on air quality. *Journal of Environmental Economics and Management*, 66(3), 424-443.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200-230.

Chen, J., Chen, W., Liu, E., Luo, J., & Song, Z. M. (2022a). The economic cost of locking down like China: Evidence from city-to-city truck flows. Working Paper. https://michaelzsong.weebly.com/uploads/4/8/1/4/48141215/truck_flow_and_covid19_220422.pdf.

Chen, J., Shi, X., & Zhang, M. A. (2022b). Centralization of environmental administration and air pollution: Evidence from China. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4092137.

Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, 3(4), 152-185.

Deng, H., Gan, T., & Tu, Z. (2021). China's road to atmospheric environment governance: Based on the analysis of the central supervision of environmental protection system. *China Economic Quarterly*, 21(05), 1591-1614. (in Chinese)

Fu, S., & Gu, Y. (2017). Highway toll and air pollution: Evidence from Chinese cities. *Journal of Environmental Economics and Management*, 83, 32-49.

Feng, T., Du, H., Mi, Z., Chen, Z., & Wang, N. (2022). The effects of environmental inspection on air quality: Evidence from China. *Journal of Cleaner Production*, 378, 134496.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *Quarterly Journal of Economics*, 110(2), 353-377.

Ghanem, D., & Zhang, J. (2014). 'Effortless Perfection:'Do Chinese cities manipulate air pollution data?. *Journal of Environmental Economics and Management*, 68(2), 203-225.

Gibson, J., Olivia, S., Boe-Gibson, G., & Li, C. (2021). Which night lights data should we use in economics, and where?. *Journal of Development Economics*, 149, 102602.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, 225(2), 254-277.

Greenstone, M., He, G., Li, S., & Zou, E. Y. (2021). China's war on pollution: Evidence from the first 5 years. *Review of Environmental Economics and Policy*, 15(2), 281-299.

Greenstone, M., He, G., Jia, R., & Liu, T. (2022). Can technology solve the principal-agent problem? Evidence from China's war on air pollution. *American Economic Review: Insights*, 4(1), 54-70.

Henderson, J. V., Storeygard, A., & Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2), 994-1028.

Holz, C. A. (2013). Chinese statistics: Classification systems and data sources. *Eurasian Geography and Economics*, 54(5-6), 532-571.

Jia, R. (2017). Pollution for promotion. Working Paper. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3029046.

Jia, K., & Chen, S. (2019). Could campaign-style enforcement improve environmental performance? Evidence from China's central environmental protection inspection. *Journal of Environmental Management*, 245, 282-290.

Li, H., & Zhou, L. A. (2005). Political turnover and economic performance: the incentive role of personnel control in China. *Journal of Public Economics*, 89(9-10), 1743-1762.

Lai, W. (2017). Pesticide use and health outcomes: Evidence from agricultural water pollution in China. *Journal of Environmental Economics and Management*, 86, 93-120.

Lin, J., Long, C., & Yi, C. (2021). Has central environmental protection inspection improved air quality? Evidence from 291 Chinese cities. *Environmental Impact Assessment Review*, 90, 106621.

Li, S., Wang, M., & Zhang, D. (2022). Environmental inspection and firm entry: Evidence from firm registration data. *Journal of World Economy*, 45(01), 110-132. (in Chinese)

Myerson, R. B. (1979). Incentive compatibility and the bargaining problem. *Econometrica*, 61-73.

Nie, H., Han, D., Ma, L., & Zhang, N. (2020). China City Political and Business Relations Ranking 2020. Research Report of National Academy of Development and Strategy, Renmin University of China. http://www.niehuihua.com/a/chuban/557.html. (in Chinese)

Kostka, G., & Nahm, J. (2017). Central–local relations: Recentralization and environmental governance in China. *China Quarterly*, 231, 567-582.

Karplus, V. J., & Wu, M. (2019). Crackdowns in hierarchies: Evidence from China's environmental inspections. Working Paper. https://extranet.sioe.org/uploads/sioe2020/karplus_wu.pdf.

Qiu, Y., Chen, X., & Shi, W. (2020). Impacts of social and economic factors on the transmission of coronavirus disease 2019 (COVID-19) in China. *Journal of Population Economics*, 33, 1127-1172.

Radner, R. (1985). Repeated principal-agent games with discounting. *Econometrica*, 1173-1198.

Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. *World Development*, 32(8), 1419-1439.

Soytas, U., & Sari, R. (2007). The relationship between energy and production: Evidence from Turkish manufacturing industry. *Energy Economics*, 29(6), 1151-1165.

Sun, S., & Anwar, S. (2015). Electricity consumption, industrial production, and entrepreneurship in Singapore. *Energy Policy*, 77, 70-78.

Tan, Y., & Mao, X. (2021). Assessment of the policy effectiveness of Central Inspections of Environmental Protection on improving air quality in China. *Journal of Cleaner Production*, 288, 125100.

Wang, H., Zhao, L., Xie, Y., & Hu, Q. (2016). "APEC blue"—the effects and implications of joint pollution prevention and control program. *Science of the Total Environment*, 553, 429-438.

Wang, L., Liu, X., & Xiong, Y. (2019). Central environmental protection inspector and air pollution governance: An empirical analysis based on micro-panel data of prefecture-level cities. *China Industrial Economics*, 10, 5-22. (in Chinese)

Wang, X., Si, C., Gu, J., Liu, G., Liu, W., Qiu, J., & Zhao, J. (2021a). Electricity-consumption data reveals the economic impact and industry recovery during the pandemic. *Scientific Reports*, 11(1), 19960.

Wang, W., Sun, X., & Zhang, M. (2021b). Does the central environmental inspection effectively improve air pollution?-An empirical study of 290 prefecture-level cities in China. *Journal of Environmental Management*, 286, 112274.

Wang, S., Zhang, R., Wan, L., & Chen, J. (2023). Has central government environmental protection interview improved air quality in China?. *Ecological Economics*, 206, 107750.

Yao, J. (2021). Electricity consumption and temperature: Evidence from satellite data. IMF Working Paper. https://www.elibrary.imf.org/view/journals/001/2021/022/article-A001-en.xml/.

Yuan, F., Zhai, Y., Sun, X., & Dong, Y. (2022). Air pollution mitigation: Evidence from China's central environmental inspection. *Environmental Impact Assessment Review*, 96, 106835.

Zhang, X., Zhang, X., & Chen, X. (2017). Happiness in the air: How does a dirty sky affect mental health and subjective well-being?. *Journal of Environmental Economics and Management*, 85, 81-94.

Zhang, B., Chen, X., & Guo, H. (2018a). Does central supervision enhance local environmental enforcement? Quasi-experimental evidence from China. *Journal of Public Economics*, 164, 70-90.

Zhang, P., Deschenes, O., Meng, K., & Zhang, J. (2018b). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88, 1-17.

Zheng, L., & Na, M. (2020). A pollution paradox? The political economy of environmental inspection and air pollution in China. *Energy Research & Social Science*, 70, 101773.

Zou, E. Y. (2021). Unwatched pollution: The effect of intermittent monitoring on air quality. *American Economic Review*, 111(7), 2101-2126.

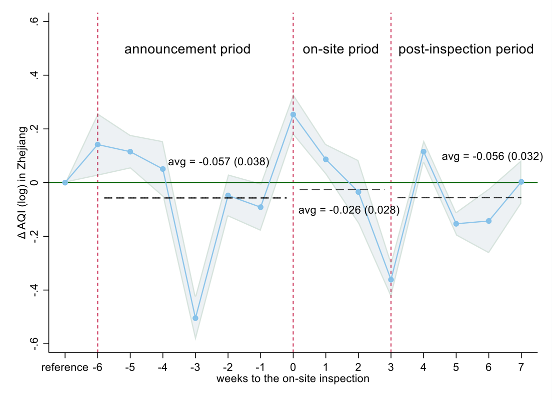
Appendix

Figures

Figure A1: Effects of the second round of CEPI on air quality- by Zhejiang and Jiangsu

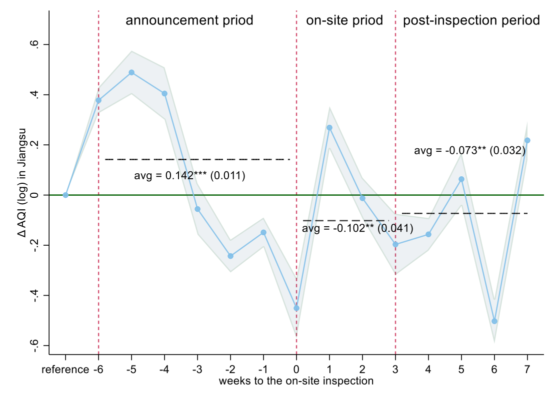
Panel A: Zhejiang Province

(A) AQI

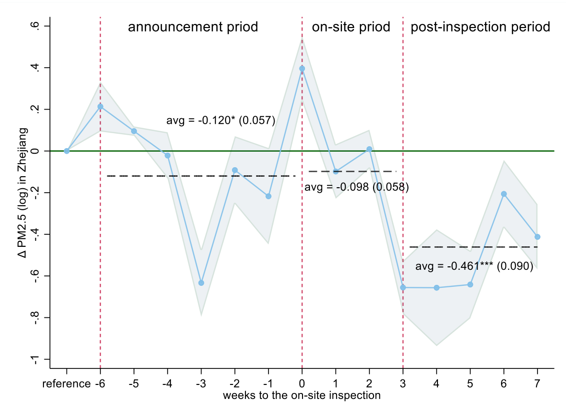


Panel B: Jiangsu Province

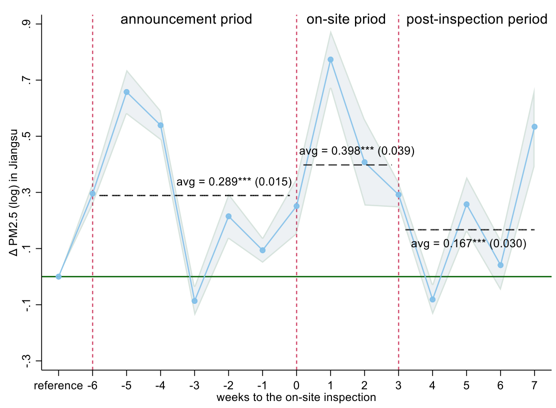
(A) AQI



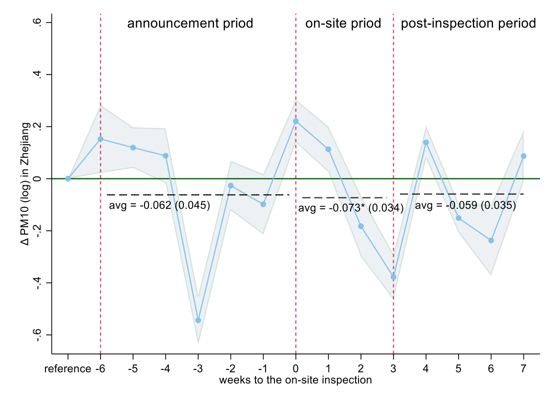
(B) PM2.5



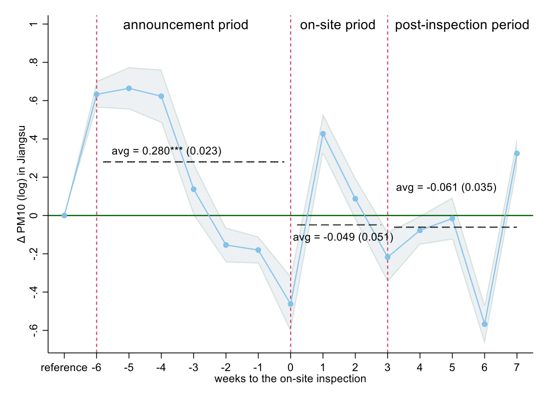
(B) PM2.5



(C) PM10



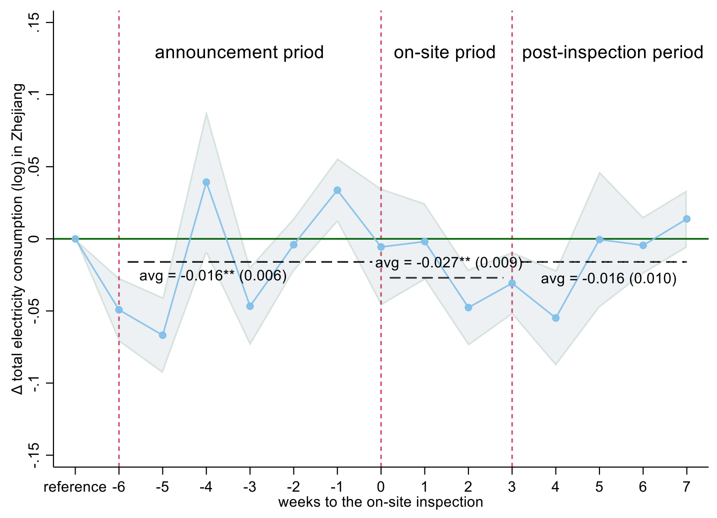
(C) PM10



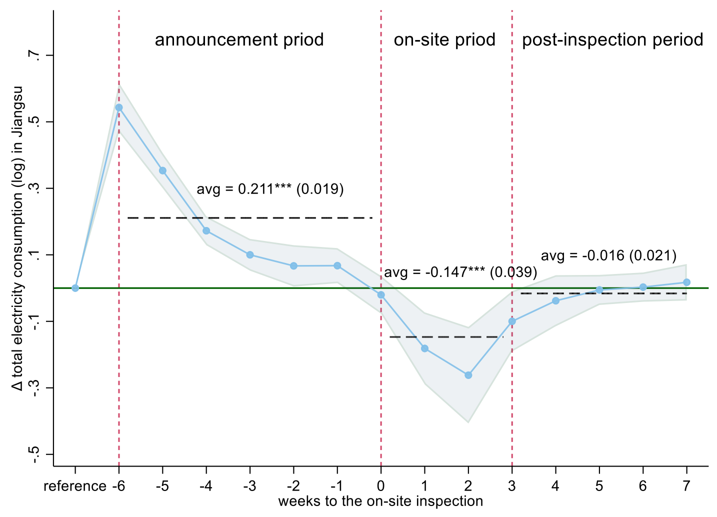
Notes: The blue dots represent coefficients for each week compared to reference weeks (7-12 weeks before the arrival of CEPI) estimated by Equation (1). The shaded area represents the 95% confidence interval. Average policy effects during different stages of CEPI are estimated by Equation (2) and represented by black dashed lines. Standard errors clustered at the city level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A2: Effects of the second round of CEPI on total electricity consumption- by Zhejiang and Jiangsu

Panel A: Zhejiang Province

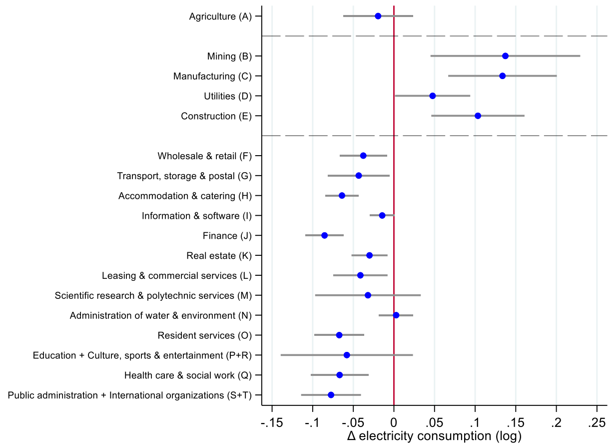


Panel B: Jiangsu Province

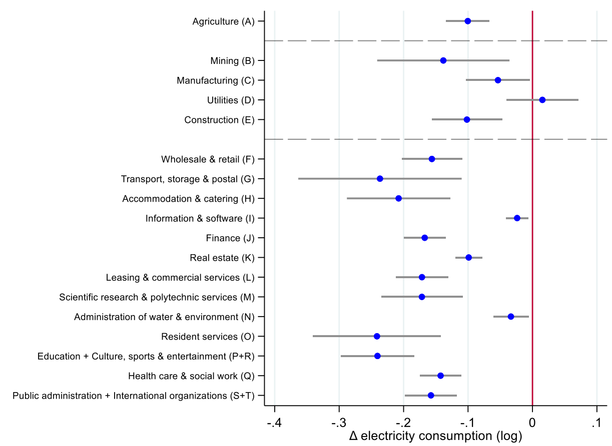


Notes: The blue dots represent coefficients for each week compared to reference weeks (7-12 weeks before the arrival of CEPI) estimated by Equation (1). The shaded area represents the 95% confidence interval. Average policy effects during different stages of CEPI are estimated by Equation (2) and represented by black dashed lines. Standard errors clustered at the city level are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

(A) Announcement effects



(B) On-site inspection effects



(C) Post-inspection effects

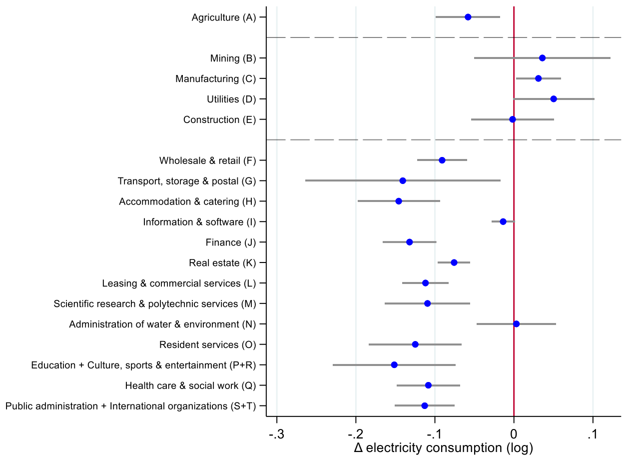


Figure A3: Industry heterogeneity of CEPI effects

Notes: The blue dots represent point estimates of average policy effects in each industry following Equation (2). The solid gray lines represent the 95% confidence interval. In all Panels, the reference period is 7-12 weeks before the arrival of CEPI. Industry codes are presented in parentheses, which are consistent with the classification of GB/T4754-2011. Standard errors are clustered at the city level.

Tables

Table A1: Time of arrival and leave of the inspectors

Province	The first round of CEPI		Revisit of the first round of CEPI		The second round of CEPI	
	arrival date	leave date	arrival date	leave date	arrival date	leave date
Beijing	2016.11.29	2016.12.29	No		2020.8.31	2020.9.30
Tianjin	2017.4.28	2017.5.28	No		2020.8.30	2020.9.30
Hebei	2016.1.4	2016.2.4	2018.5.31	2018.6.30	2022.3.23	2022.4.23
Shanxi	2017.4.28	2017.5.28	2018.11.6	2018.12.6	2021.4.7	2021.5.7
Inner Mongolia	2016.7.14	2016.8.14	2018.6.6	2018.7.6	2022.3.25	2022.4.25
Heilongjiang	2016.7.19	2016.8.19	2018.5.30	2018.6.30	2021.12.3	2022.1.3
Jilin	2017.8.11	2017.9.11	2018.11.5	2018.12.5	2021.8.26	2021.9.26
Liaoning	2017.4.25	2017.5.25	2018.11.4	2018.12.4	2021.4.6	2021.5.6
Shanghai	2016.11.28	2016.12.28	No		2019.7.11	2019.8.11
Shandong	2017.8.10	2017.9.10	2018.11.1	2018.12.1	2021.8.26	2021.9.26
Jiangsu	2016.7.15	2016.8.15	2018.6.5	2018.7.5	2022.3.25	2022.4.25
Zhejiang	2017.8.11	2017.9.11	No		2020.9.1	2020.10.1
Anhui	2017.4.27	2017.5.27	2018.10.31	2018.11.31	2021.4.7	2021.5.7
Jiangxi	2016.7.14	2017.7.14	2018.6.1	2018.7.1	2021.4.7	2021.5.7
Fujian	2017.4.24	2017.5.24	No		2019.7.15	2019.8.15
Henan	2016.7.16	2016.8.16	2018.6.1	2018.7.1	2021.4.7	2021.5.7
Hubei	2016.11.26	2016.12.26	2018.10.30	2018.11.30	2021.8.31	2021.9.30
Hunan	2017.4.24	2017.5.24	2018.10.30	2018.11.30	2021.4.6	2021.5.6
Guangdong	2016.11.28	2016.12.28	2018.6.5	2018.7.5	2021.8.27	2021.9.27
Guangxi	2016.7.14	2016.8.14	2018.6.7	2018.7.7	2021.4.9	2021.5.9
Hainan	2017.8.10	2017.9.10	No		2019.7.14	2019.8.14
Chongqing	2016.11.24	2016.12.24	No		2019.7.12	2019.8.12
Sichuan	2017.8.7	2017.9.7	2018.11.3	2018.12.3	2021.8.26	2021.9.26
Guizhou	2017.4.26	2017.5.26	2018.11.4	2018.12.4	2021.12.5	2022.1.5
Yunnan	2016.7.15	2016.8.15	2018.6.5	2018.7.5	2021.4.6	2021.5.6
Xizang	2017.8.15	2017.9.15	No		2022.3.25	2022.4.25
Shaanxi	2016.11.28	2016.12.28	2018.11.3	2018.12.3	2021.12.4	2022.1.4
Gansu	2016.11.30	2016.12.30	No		2019.7.12	2019.8.12
Ningxia	2016.7.12	2016.8.12	2018.6.1	2018.7.1	2021.12.3	2022.1.3
Qinghai	2017.8.8	2017.9.8	No		2019.7.14	2019.8.14
Xinjiang	2017.8.11	2017.9.11	No		2022.3.25	2022.4.25

Notes: The arrival and leave time of CEPI is from the official website of the MEE.
See: https://www.mee.gov.cn/ywgz/zysthjbhdc/dcjz.

Table A2: County units of electricity consumption data

Panel A: Zhejiang Province

Prefecture-level city	County unit	Prefecture-level city	County unit
Lishui	Yunhe, Qingyuan, Jingning, Songyang, Jinyun, Liandu, Suichang, Qingtian, Longquan	Huzhou	Nanxun, Wuxing, Anji, Deqing, Changxing
Taizhou	Sanmen, Linhai, Xianju, Tiantai, Jiaojiang, Wenling, Yuhuan, Luqiao, Huangyan	Shaoxing	Shangyu, Shengzhou, Xinchang, Keqiao, Zhuji, Yuecheng
Jiaxing	Nanhu, Jiashan, Pinghu, Tongxiang, Haining, Haiyan, Xiuzhou	Zhoushan	Dinghai, Daishan, Shengsi, Putuo
Ningbo	Yuyao, Beilun, Fenghua, Ninghai, Cixi, Jiangbei, Haishu, Xiangshan, Yinzhou, Zhenhai	Quzhou	Changshan, Kaihua, Kecheng, Jiangshan, Qujiang, Longyou
Hangzhou	Shangcheng, Linan, Linping, Yuhang, Fuyang, Jiande, Gongshu, Tonglu, Chunan, Binjiang, Xiaoshan, Xihu, Qiantang	Jinhua	Dongyang, Yiwu, Lanxi, Wucheng, Wuyi, Yongkang, Pujiang, Panan, Jindong
Wenzhou	Leqing, Pingyang, Wencheng, Yongjia, Taishun, Dongtou, Ruian, Ouhai, Cangnan, Lucheng, Longgang, Longwan		

Panel B: Jiangsu Province

Prefecture-level city	County unit	Prefecture-level city	County unit
Nanjing	*Shixiaqu*, Lishui, Gaochun	Taizhou	*Shixiaqu*, Xinghua, Jiangyan, Taixing, Jingjiang
Nantong	*Shixiaqu*, Qidong, Rudong, Rugao, Haian, Haimen, Tongzhou	Huaian	*Shixiaqu*, Hongze, Lianshui, Xuyi, Jinhu
Suqian	*Shixiaqu*, Shuyang, Sihong, Siyang	Yancheng	*Shixiaqu*, Dongtai, Xiangshui, Dafeng, Sheyang, Binhai, Funing
Changzhou	*Shixiaqu*, Liyang, Jintan	Suzhou	*Shixiaqu*, Wujiang, Taicang, Changshu, Zhangjiagang, Kunshan
Xuzhou	*Shixiaqu*, Fengxian, Xinyi, Peixian, Suining, Pizhou, Tongshan	Lianyungang	*Shixiaqu*, Donghai, Guanyun, Guannan, Ganyu
Yangzhou	*Shixiaqu*, Yizheng, Baoying, Jiangdu, Gaoyou	Zhenjiang	*Shixiaqu*, Danyang, Jurong, Yangzhong
Wuxi	*Shixiaqu*, Yixing, Jiangyin		

Notes: 'County unit' refers to counties or districts included in empirical analysis. '*Shixiaqu*' includes all municipal districts in each city in Jiangsu Province.

Table A3: Summary statistics by pseudo-CEPI periods

	Reference weeks (7-12 weeks before the pseudo-arrival of central inspectors)	Announcement period (1-6 weeks before the pseudo-arrival of central inspectors)	On-site period (0-3 weeks before the pseudo-arrival of central inspectors)	Post-CEPI period (4-7 weeks before the pseudo-arrival of central inspectors)
Observations	6,468	6,468	4,312	4,312
Electricity consumption				
Total production electricity consumption: million kWh	9.552	8.987	9.831	9.810
	(19.499)	(18.089)	(19.160)	(19.503)
Primary industry consumption: million kWh	0.032	0.031	0.030	0.030
	(0.051)	(0.045)	(0.044)	(0.047)
Secondary industry consumption: million kWh	7.263	7.042	8.023	7.953
	(14.385)	(13.973)	(15.383)	(15.442)
Tertiary industry consumption: million kWh	2.257	1.914	1.779	1.827
	(6.110)	(5.009)	(4.719)	(5.040)
Air quality				
AQI: 1-500	57.106	48.754	59.929	56.904
	(32.211)	(25.516)	(43.436)	(30.080)
PM2.5: μg/m^3	32.794	27.704	26.836	33.035
	(16.109)	(13.784)	(11.295)	(13.170)
PM10: μg/m^3	59.316	49.123	64.835	61.472
	(40.575)	(36.444)	(66.349)	(46.207)
Weather				
Temperature: °C	16.938	20.951	20.640	20.199
	(10.980)	(9.893)	(5.555)	(3.316)
Precipitation: mm	6.353	5.082	1.585	2.156
	(14.291)	(14.733)	(4.766)	(5.590)
Wind speed: m/s	1.970	2.372	2.265	2.070
	(0.769)	(1.073)	(1.018)	(0.810)
Relative humidity: %	77.057	74.360	71.486	74.666
	(16.082)	(13.371)	(13.633)	(12.799)
Atmospheric pressure: hPa	1.970	2.372	2.265	2.070
	(0.769)	(1.073)	(1.018)	(0.810)
COVID-19 cases				
# of new confirmed cases: people	0	0	0	0
	(0)	(0)	(0)	(0)
# of cumulative confirmed cases: people	20.201	20.201	20.201	20.201
	(28.992)	(28.992)	(28.993)	(28.993)

Notes: Table A3 presents the means and standard deviations (in parentheses) of variables during the pseudo-CEPI periods. Dates that the central inspection teams arrive are assumed one year earlier than the real dates. The inspection team is assumed to arrive in Zhejiang on September 1, 2019, and in Jiangsu on March 25, 2021. The data from Zhejiang and Jiangsu are pooled together to produce Table A3.

Table A4: Effects of the second round of CEPI on air quality and production-side electricity consumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	log(AQI)	log(PM2.5)	log(PM10)	log(total electricity consumption)	log(primary industry electricity consumption)	log(secondary industry electricity consumption)	log(tertiary industry electricity consumption)
				Panel A: week-by-week effects			
week -6	0.220***	0.274***	0.308***	0.187***	-0.034	0.259***	0.039
	(0.040)	(0.038)	(0.061)	(0.061)	(0.033)	(0.074)	(0.038)
week -5	0.237***	0.385***	0.305***	0.074*	-0.086**	0.112**	-0.023
	(0.042)	(0.068)	(0.062)	(0.043)	(0.033)	(0.050)	(0.029)
week -4	0.203***	0.169**	0.333***	0.109***	-0.028	0.161***	-0.035***
	(0.045)	(0.064)	(0.059)	(0.023)	(0.018)	(0.029)	(0.009)
week -3	-0.312***	-0.371***	-0.248***	0.038**	-0.069***	0.082***	-0.093***
	(0.054)	(0.072)	(0.077)	(0.018)	(0.018)	(0.024)	(0.008)
week -2	-0.131***	0.000	-0.117***	0.037***	-0.033*	0.085***	-0.091***
	(0.033)	(0.054)	(0.035)	(0.013)	(0.017)	(0.017)	(0.010)
week -1	-0.112***	-0.105	-0.156***	0.048***	-0.025	0.086***	-0.035***
	(0.030)	(0.066)	(0.039)	(0.010)	(0.015)	(0.013)	(0.010)
week 0	-0.041	0.311***	-0.119	0.002	-0.006	0.025	-0.055***
	(0.078)	(0.034)	(0.073)	(0.016)	(0.021)	(0.017)	(0.017)
week 1	0.157***	0.241**	0.233***	-0.075***	-0.138***	-0.045	-0.167***
	(0.030)	(0.093)	(0.045)	(0.026)	(0.019)	(0.034)	(0.017)
week 2	-0.025	0.113*	-0.016	-0.140***	-0.180***	-0.137***	-0.184***
	(0.034)	(0.065)	(0.044)	(0.033)	(0.026)	(0.041)	(0.021)
week 3	-0.321***	-0.238**	-0.328***	-0.053***	-0.147***	-0.014	-0.145***
	(0.032)	(0.097)	(0.032)	(0.018)	(0.026)	(0.020)	(0.012)
week 4	-0.013	-0.415***	-0.008	-0.041**	-0.076***	-0.008	-0.117***
	(0.032)	(0.092)	(0.027)	(0.016)	(0.027)	(0.019)	(0.011)

week 5	-0.097***	-0.279***	-0.184***	0.019	-0.043*	0.069***	-0.098***
	(0.033)	(0.096)	(0.030)	(0.019)	(0.022)	(0.023)	(0.017)
week 6	-0.284***	-0.094	-0.342***	0.010	-0.091***	0.043***	-0.065***
	(0.049)	(0.058)	(0.051)	(0.010)	(0.024)	(0.013)	(0.010)
week 7	0.078**	-0.070	0.146***	0.030***	-0.088***	0.069***	-0.055***
	(0.034)	(0.095)	(0.042)	(0.010)	(0.025)	(0.012)	(0.012)
R^2	0.632	0.441	0.646	0.990	0.989	0.984	0.995
			Panel B: average effects during CEPI stages				
Announcement period	0.019	0.048	0.067	0.079***	-0.047***	0.125***	-0.038***
	(0.031)	(0.055)	(0.046)	(0.024)	(0.015)	(0.030)	(0.011)
On-site period	-0.055**	0.098	-0.060**	-0.076***	-0.116***	-0.056**	-0.138***
	(0.022)	(0.062)	(0.025)	(0.020)	(0.019)	(0.023)	(0.015)
Post-CEPI period	-0.068***	-0.204**	-0.086***	-0.007	-0.075***	0.028**	-0.085***
	(0.018)	(0.080)	(0.020)	(0.011)	(0.023)	(0.013)	(0.011)
R^2	0.576	0.396	0.598	0.989	0.989	0.983	0.995
Control variables	Y	Y	Y	Y	Y	Y	Y
Time trend	Y	Y	Y	Y	Y	Y	Y
Date characteristics	Y	Y	Y	Y	Y	Y	Y
County-by-year FE	Y	Y	Y	Y	Y	Y	Y
City-by-month FE	Y	Y	Y	Y	Y	Y	Y

Notes: Observations are 43,120 for all regressions. Reference weeks are 7-12 weeks before the on-site inspection. Control variables include weather controls and the cumulative number of confirmed COVID-19 cases. Time trend is a fourth-order time polynomial. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Robustness checks

	log (total electricity consumption)						
	(1) Baseline	(2) Time polynomial order: 1	(3) Time polynomial order: 2	(4) Time polynomial order: 3	(5) Time polynomial order: 5	(6) Relaxed fixed effects	(7) Change the measurement of COVID-19
Announcement period	0.079***	0.077***	0.081***	0.079***	0.078***	0.066***	0.072***
	(0.024)	(0.024)	(0.025)	(0.024)	(0.024)	(0.023)	(0.023)
On-site period	-0.076***	-0.079***	-0.073***	-0.074***	-0.076***	-0.102***	-0.092***
	(0.020)	(0.021)	(0.020)	(0.020)	(0.020)	(0.027)	(0.023)
Post-CEPI period	-0.007	-0.010	-0.003	-0.005	-0.006	-0.042**	-0.026**
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.017)	(0.012)
Polynomial order of time trend	4	1	2	3	5	4	4
COVID-19 measurement	# cumulative confirmed cases	# cumulative confirmed cases	# cumulative confirmed cases	# cumulative confirmed cases	# cumulative confirmed cases	# cumulative confirmed cases	# new confirmed cases
Weather controls	Y	Y	Y	Y	Y	Y	Y
Date characteristics	Y	Y	Y	Y	Y	Y	Y
County-by-year FE	Y	Y	Y	Y	Y	N	Y
City-by-month FE	Y	Y	Y	Y	Y	N	Y
County FE	N	N	N	N	N	Y	N
Month FE	N	N	N	N	N	Y	N
Year FE	N	N	N	N	N	Y	N
Observations	43,120	43,120	43,120	43,120	43,120	43,120	43,120
R^2	0.989	0.989	0.989	0.989	0.989	0.982	0.989

Notes: Reference weeks are 7-12 weeks before the on-site inspection. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.

Appendix Table A6 presents which sub-sectors in the tertiary industry are grouped into producer/consumer service industries, following the classification set by the National Bureau of Statistics. However, due to the sector resolution of electricity consumption data, not all sub-sectors in the tertiary sector are grouped into the producer or consumer service industry. For example, the sector 'Wholesale and retail trades' includes both the sub-sector 'Wholesale trade' attributes to the producer service and the sub-sector 'Retail trade' attributes to the consumer service. However, we only have electricity consumption data for the sector 'Wholesale and retail trades' and do not have data for sub-sectors. For sub-sectors like that, we label them "not applicable (NA)" in Appendix Table A6, and data for them are not included to produce Figure 4. The industry codes in Appendix Table A6 are from the GB/T4754-2011 industry classification, and Holz (2013) provides an English cross-reference to that.

Table A6: Classification of sub-sectors in the tertiary industry

Sector	Producer (P)/ Consumer (C) services / Not Applicable (NA)	Sub-sector	Producer (P)/ Consumer (C) services / Not Applicable (NA)
		(A5) Agricultural services	P
		(B11) Ancillary mining activities	P, but data are not available
		(C43) Repair of metal products, machinery, and equipment	P
(F) Wholesale and retail trades	NA		
(G) Transport, storage, and postal services		(G53) Railway transport	P
		(G54) Road transport	P
		(G55) Water transport	P
		(G56) Air transport	P
		(G57) Pipeline transport	P
		(G58) Loading/unloading, removal, and other transport services	P
		(G59) Storage	NA
		(G60) Postal services	C
(H) Accommodation and catering	C		
(I) Information transfer, software, and information technology services		(I63) Telecommunications, radio, television, and satellite transmission services	NA
		(I64) Internet and related services	NA
		(I65) Software and information technology services	NA
(J) Finance	NA		

(K) Real estate	C		
(L) Leasing and commercial services	NA		
(M) Scientific research and polytechnic services	P		
(N) Administration of water, environment, and public facilities	C		
(O) Resident, repair, and other services	C		
(P) Education	C		
(Q) Health care and social work	C		
(R) Culture, sports, and enterainment	C		
(S) Public administration, social insurance, and social organizations	C		
(T) International organizations	C		

Notes: The sub-sector *(B11) Ancillary mining activities* is included in the tertiary industry according to the classification by the NBS. However, data for sub-sector B11 are not available in the electricity consumption dataset and thus cannot be used to produce Figure 4.

Table A7: Classification of industries in electricity consumption data

Industry code in GB/T4754-2011	Industry name	Industry code in the electricity consumption data	Industry name
A	Agriculture	A	Agriculture
B	Mining	B	Mining
C	Manufacturing	C	Manufacturing
D	Utilities	D	Utilities
E	Construction	E	Construction
F	Wholesale and retail trades	F	Wholesale and retail trades
G	Transport, storage, and postal services	G	Transport, storage, and postal services
H	Accommodation and catering	H	Accommodation and catering
I	Information transfer, software and information technology services	I	Information transfer, software and information technology services
J	Finance	J	Finance
K	Real estate	K	Real estate
L	Leasing and commercial services	L	Leasing and commercial services
M	Scientific research and polytechnic service	M	Scientific research and polytechnic service
N	Administration of water, environment, and public facilities	N	Administration of water, environment, and public facilities
O	Resident, repair, and other services	O	Resident, repair, and other services
P	Education	P + R	Education + Culture, sports and entertainment
Q	Health care and social work	Q	Health care and social work
R	Culture, sports and entertainment		
S	Public administration and social organizations	S + T	Public administration and social organizations + International organizations
T	International organizations		

Table A8: Classification of sub-sectors in the secondary industry

Industry code in GB/T4754-2011	Industry name	Sub-sector code in GB/T4754-2011	Sub-sector name
B	**Mining**		
		B6	Coal mining
		B7	Oil & gas exploration
		B8	Ferrous metal mining
		B9	Non-ferrous metal mining
		B10	Non-metallic mining
		B12	Other mining
C	**Manufacturing**		
		C13	Agro-food processing
		C14	Food processing
		C15	Beverage
		C16	Tobacco
		C17	Textiles
		C18	Clothes, shoes & hats
		C19	Leather
		C20	Timber
		C21	Furniture
		C22	Paper
		C23	Printing
		C24	Stationery
		C25	Petroleum product processing
		C26	Chemicals
		C27	Medicines
		C28	Chemical fiber
		C29	Rubber & plastics
		C30	Non-metallic minerals
		C31	Ferrous metal smelting
		C32	Non-ferrous metal smelting
		C33	Metal products
		C34	General equipment
		C35	Special equipment
		C36	Automobiles
		C37	Transport equipment
		C38	Electrical machinery & equipment
		C39	Communication equipment
		C40	Measuring instruments
		C41	Other manufacturing
		C42	Reuse of waste resources
		C43	Repair of metal products & machinery

D	**Utilities**		
		D44	Electricity & heat
		D45	Gas
		D46	Tap water
E	**Construction**		
		E47	Construction of buildings
		E48	Civil engineering
		E49	Renovation
		E50	Decoration

Notes: All sub-sectors in this table are covered by the electricity consumption database and are used to produce Figure 6.

Table A9: Moderating effects of political-business relationship sub-indexes on responses

Explained variable: log (total electricity consumption)			CEPI stages		
			Announcement period	On-site inspection period	Post-inspection period
Sub-indexes	*closeness indexes*	Government care	-0.0005	0.0018	-0.0011
			(0.0018)	(0.0023)	(0.0008)
		Government service	0.0002	0.0017	-0.0015
			(0.0023)	(0.0028)	(0.0011)
		Tax burden	-0.0003	-0.0002	0.0000
			(0.0014)	(0.0019)	(0.0010)
	cleanliness indexes	Government integrity	-0.0020	0.0024	-0.0013**
			(0.0012)	(0.0016)	(0.0006)
		Government transparency	-0.0053**	0.0070**	-0.0019
			(0.0023)	(0.0028)	(0.0014)

Notes: Appendix Table A9 shows moderate effects of sub-indexes of "closeness" and "cleanliness" on policy effects during different CEPI stages. Data are at the prefectural cities level and are from the " China City Political and Business Relations Ranking 2020" published by Nie et al. (2020). Sub-indexes are scaled from 1 to 100, with higher values indicating a higher level of government care, service, integrity, and transparency. A higher value of the sub-index "Tax burden" donates a lighter tax burden for enterprises in the city. For the constitution of these sub-indexes, see Nie et al. (2020). Each result in the table is obtained from a separate regression. The table only reports the results of interactions between sub-indexes and $CEPI\_stage_{cd} \times \mathbf{1}(CEPI_{cy})$. The model specification for producing Appendix Table A9 is the same as in Table 4 . The reference period for the announcement effect is 7-12 weeks before the arrival of CEPI. The reference period for the on-site inspection effect is the announcement period. The reference period for the post-inspection effect is the on-site inspection period. Standard errors are clustered at the city level. *** p<0.01, ** p<0.05, * p<0.1.