Strategic Capture of Monitors: Evidence from Pollution Control in China

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Abstract

Third-party monitors are commonly deployed to mitigate agency problems in multi-layered organizations. Yet these third-party relationships may themselves be subject to agency concerns, and monitors coopted by the entities they oversee. We examine how third-party monitoring can be undermined by collusion between monitor and agent, in the context of pollution monitoring in China. We exploit an outsourcing reform that transferred the operation and maintenance (O&M) of pollution monitoring stations from local governments to third-party firms selected by the central government. We find that local governments significantly increased procurement transactions with their assigned O&M firms post-reform. Additionally, following these transactions, reported air pollution from monitoring stations declined, as did enforcement actions against nearby polluting firms. Our results suggest that oversight was undermined by collusive arrangements of monitors and agents.

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1 Introduction

Delegated third-party monitors are a common means of mitigating agency problems in decentralized organizations.The efficacy of this approach hinges on the extent to which these monitors operate independently and report truthfully. However, in both private and public sector settings, these ostensibly independent watchdogs have the potential to be co-opted by the entities they are charged with monitoring.

While the problem of firms co-opting their monitors has been studied by economists and accounting researchers (Duflo et al., 2013; Pierce and Toffel, 2013; Causholli, Chambers and Payne, 2014; Short, Toffel and Hugill, 2016), little work has focused on the analogous problem in the public sector. The issue is extremely relevant to the functioning and oversight of decentralized governments, which are often overseen by ostensibly independent monitors; yet we know very little about whether and how such watchdogs can be compromised.

This paper studies the question of third-party monitoring of local air pollution in China. We exploit a 2016 change in central government policy, which shifted control over air quality data collection from city governments to third-party operators.[1]

Since 2005, city leaders in China have been evaluated in part based on adherence to national environmental objectives, which can sometimes conflict with incentives based on local economic growth (Chen, Li and Lu, 2018). This multitask incentive structure led to concerns that local governments were manipulating pollution data (e.g., by spraying water near monitoring stations) to improve air quality measures without having to reduce industrial output.

The solution proposed by the central government was to take control of the operation and maintenance (O&M) of air quality monitoring stations away from local environmental authorities, and reassign this responsibility to private firms. While the new system reduced the scope for direct data manipulation by the local government, it may also have introduced new and

[1] Throughout the paper, we use the terms "city" to describe the administrative unit that is our focus, which is prefecture-level administrative divisions in China. Our sample include prefecture-level cities, the four centrally administered municipalities (Beijing, Shanghai, Tianjin, and Chongqing), as well as non-municipal prefectures such as autonomous prefectures and leagues.

indirect opportunities for manipulation. Specifically, just as private sector auditors may be motivated to be lenient if they wish to attract non-audit business from the companies they monitor (Causholli, Chambers and Payne, 2014), governments may collude with O&M operators to extract more favorable air quality readings by offering these operators government procurement contracts.

The reform was implemented in 2016. As shown in Figure 1, a total of 12 lots were up for bid, each of which included O&M responsibility for prefectures spread in clusters throughout the country.[2] All eligible bidders were major suppliers of environmental monitoring equipment, with national rather than regional footprints. The auction rules stipulated that a total of six firms would receive two contracts each, through an assignment mechanism described in more detail in Section 2. In each city, the assigned firm was tasked with ensuring that local stations functioned autonomously and that reported air quality data was not subject to local interference. The reform thus generated cross-sectional variation in the identity of the firm responsible for each city's monitoring stations.[3]

In our analysis, we begin by presenting the time series patterns for air quality reported by monitoring stations and, as a point of comparison, satellite-based measures of air quality. The latter, while much less precise, serves as a benchmark that is not subject to manipulation in the same way as data from a land-based station. We show that, while satellite-based measures remained flat after an initial post-reform drop, air pollution as reported by monitoring stations trended downward in the years that followed. With these broad patterns as motivation, we turn to exploring the potential role of city-firm collusion in driving the continued decline in ground-based (but not satellite) measures of air pollution. We posit that collusion occurs through the assignment of procurement contracts to the firm with O&M responsibility for a city. We define "related procurement" as contracts assigned by a prefecture to this firm, and 'unrelated procurement" as contracts assigned to any of the other five designated O&M firms.

First, we document that there is a large and significant increase in "re-

[2]Each lot typically spanned multiple provinces; the prefectures within the same province were usually split across different contracts, though in a few cases an entire province was grouped into a single contract.

[3]We confirm below that assignment to a particular firm is uncorrelated with any pre-assignment city attribute, including economic as well as environmental characteristics.

lated procurement" following the implementation of the reform: after the reform was initiated at the beginning of 2016, the probability that a related firm had been awarded a contract increases by 16.6 percentage points, a very large impact relative to the base rate of 12.5%. This suggests an effort by local governments to strategically deepen ties with their assigned monitoring contractors, which offered a channel through which they could exert informal influence over watchdogs that were formally independent. To link this result more directly to city leaders' incentives, we exploit discontinuities in promotion opportunities induced by mandatory retirement leaders' ages at the time of the National People's Congress (NPC). Our main result is driven by those who would be 57 years old and younger at the time of the NPC, who are eligible for promotion, whereas we observe no effect of the reform on related procurement for those 58 and older.[4]

To examine the consequences of related procurement, we assess how air pollution changes around the signing of related contracts between a city and its assigned O&M firm. We observe a clearly discernible drop in air pollution as reported by the monitoring stations managed by the firm, but no change in satellite-based air pollution measures. We argue that, if anything, the endogenous assignment of related procurement contracts should bias these estimates toward zero, with related firms proactively reducing measured air pollution in the hope of later securing local government contracts.

We then return to consider the further implications of the multitask problem faced by city leaders, who are evaluated based on environmental as well as economic outcomes. If related contracting allows for measured environmental improvements without any actual change in air pollution, we may expect less governmental incentive to crack down on relatively high-pollution businesses. In our final set of analyses, we thus look at environmental enforcement actions against firms located near to air pollution monitoring stations.[5] We find a discrete drop in environmental enforcement for excessive air pollution for firms within a 15 kilometer radius of a monitoring station, relative to more

[4]Promotion decisions for senior prefecture leaders are typically made at the time of the NPC. Hence, the age of an official in the NPC determines whether they are still eligible for promotion. The cut-off comes from the fact that senior bureaucrats have a mandatory retirement age of 60, and must be able to serve at least three years at the time of appointment.

[5]Following Axbard and Deng (2024) we use a cutoff of 15 kilometers as the radius around a station where industrial activity could impact air quality readings, but show that our results are also robust to using a marginally smaller or larger radius.

distant (30-45 km) firms as a benchmark. (We do not observe such a change in enforcement actions related to noise or water pollution, which serves as a useful reference for changes in environmental protection in general.) Interestingly, we document an *increase* in enforcement actions against more distant firms which, owing to endogenous placement of monitoring stations, tend to be smaller and less-polluting establishments.

Our study is the first to document the strategic responses of local governments to higher-level authorities' efforts at effective monitoring through third-party agents. In doing so, we draw on a rich theoretical tradition that highlights the risk of collusion between monitors and the agents they oversee, particularly in circumstances where there is imperfect monitoring and repeated interaction (Tirole, 1986; Prendergast, 1993; Laffont and Martimort, 1997; Strausz, 1997; Rahman, 2012; Ortner and Chassang, 2018; Strulovici, 2021; Mookherjee, 2012; Mookherjee and Tsumagari, 2023). We highlight that, paralleling findings on private sector auditing (Causholli, Chambers and Payne, 2014), these risks are particularly severe in cases in which there is "multimarket contact" between the monitored party (in our case the local government) and the third-party monitor. Furthermore, research in political economy emphasizes that bureaucratic accountability hinges on credible information flows (e.g., Chang, Golden and Hill, 2010). We extend this insight by showing how collusive arrangements between local governments and monitors can undermine these flows, contributing to a nascent body of work documenting distortions in information transmission (Duflo et al., 2013; Chu et al., 2021; Vannutelli, 2022). Whereas prior work exploits exogenous sources of collusion – such as experimental variation in who hires the monitor (Duflo et al., 2013; Marion and West, 2024), personal connections (Chu et al., 2021), or institutional hiring arrangements (Vannutelli, 2022) – we document that local governments endogenously create collusive ties with monitors. This distinction highlights how agents can strategically build connections to subvert accountability even in the absence of preexisting relationships or contracting structures.

Our paper also contributes to a growing empirical literature on environmental regulation and pollution control in developing countries. Prior studies have shown that regulatory reforms (Greenstone and Hanna, 2014; Tanaka, 2015; Ebenstein et al., 2017), political incentives (Kahn, Li and Zhao, 2015; Lipscomb and Mobarak, 2016), citizen participation (Buntaine et al., 2024) and monitoring innovations (Duflo et al., 2013; Greenstone et al., 2022; Barwick et al., 2024; Yang et al., 2024) all shape pollution outcomes. In a sense, the closest antecedent is Axbard and Deng (2024), which studies the introduction of the real-time pollution monitoring technology in Chinese cities – launched at the beginning of 2015 – which serves as the starting point for our timeline. However, the research questions we pursue are quite distinct. Whereas Axbard and Deng (2024) study how the introduction of a pollution control *technology* impacted subsequent environmental outcomes, we examine the implications of principal-agent problems in the management of this technology. In this sense, we see the papers as complements, in the same way that technologies and human implementation are more generally complementary features of monitoring.[6]

More broadly, we contribute to the literature on reciprocal exchange between government and private firms (Shleifer and Vishny, 1994; Faccio, 2006; Di Tella and Franceschelli, 2011; Blanes i Vidal, Draca and Fons-Rosen, 2012; Bertrand, Bombardini and Trebbi, 2014). While this literature typically examines how firms seek to influence the state to secure favorable treatment, our paper emphasizes the other side of this relationship, with local governments engaging private firms to co-opt delegated monitoring institutions.

2 China's Air Quality Monitoring and Outsourcing Reforms

2.1 Empirical Context

China launched a national "war on pollution" in 2013, with the aim of combating smog and industrial emissions. To implement these goals, the State Council – China's central administrative authority – issued the Action Plan for Air Pollution Prevention and Control. The plan focused on curbing and reducing overcapacity in the coal, steel, and cement sectors, while promoting large-scale investments in pollution control technologies to reduce sulfur, nitrogen, and particulate matter emissions. To ensure accurate information for regulatory enforcement, the central government required provincial environmental bureaus to finance the construction of automated air quality

[6] See, for example, Asunka et al. (2019) on the failure of election monitoring technology in Ghana due to political intervention, and discussion of political pressure to repeal of biometric identification for accessing government subsidies in Barnwal (2024).

monitoring systems in nearly all cities. The resulting national monitoring network consists of 1,497 centrally managed stations, designed to cover the urban areas of 367 cities.

Once the equipment was in place, city-level environmental bureaus were assigned responsibility for the operation and maintenance of all monitors within their jurisdictions. Although the system was automated, data manipulation remained possible. According to reports from the Ministry of Environmental Protection (MEP), a common tactic involved spraying water near sensors to artificially lower $PM_{2.5}$ readings.[7] City leaders were incentivized to encourage this type of manipulation because they were evaluated in part based on environmental outcomes, including air pollution (see, e.g., Chen, Li and Lu, 2018). While environmental targets were designed to strengthen environmental compliance, they also created strong incentives for local officials to ensure favorable reported outcomes, particularly in cities with industrial bases where economic development and pollution control were in tension.

To insulate the monitoring process from local interference, the MEP moved to centralize control by contracting third-party private firms to operate the stations. In October 2015, the National Monitoring Center of the Ministry of Environmental Protection (acting on behalf of the central government) announced a national tender to outsource the operation of nearly all state-controlled air quality monitoring stations across China.[8] Cities were grouped into twelve bidding lots, and the O&M rights were to be assigned to 6 designated firms. Typically, a province was split into two different lots, and

[7] See `https://www.mee.gov.cn/xxgk2018/xxgk/xxgk06/201803/t20180329_629670.html`, last accessed September 30, 2025. Appendix Figure A1 displays a real example of spraying water on a monitoring station. This was not, however, the only technique. In a case uncovered in Xi'an, local officials were caught stuffing cotton or gauze into monitoring stations' particle samplers to bring the reported PM_{10} and $PM_{2.5}$ levels. When the readings became "too low," they sometimes removed the obstructions, only to reinsert them when pollution levels rose. See `https://www.thepaper.cn/newsDetail_forward_1967703`, last accessed September 30, 2025.

[8] The central government did not directly manage the monitoring stations because it lacked sufficient professional staff to operate such a large network, covering nearly 1,500 monitoring stations. Outsourcing to specialized firms through competitive tendering allowed the government to tap into technical expertise not available within the civil service. It also was expected to result in lower administrative and fiscal costs, since outsourcing would be far less expensive than maintaining a large cadre of centrally employed technicians.

the rules stipulated that no single operator could win both lots in the same province.[9] This arrangement was likely intended to facilitate comparisons across neighboring cities by assigning them to different operators. A given lot typically included cities from several geographically separated provinces. For example, lot 1 included all cities from Xinjiang (west and underdeveloped) and part of cities from Guangdong (south and well-developed), Zhejiang, and Shanghai (both central and well-developed). Other cities in these provinces were assigned different lot numbers (for example, the other cities in Zhejiang province were assigned to lot 2).

Firms were allowed to bid for multiple lots but could be awarded no more than two in total. Given that there were 12 lots and 6 firms, each winning firm was awarded exactly two lots.

Bids were evaluated lot by lot under a comprehensive scoring system, based on a range of criteria, including the firm's experience, the quality of its proposed data review and quality control plan, staffing arrangements, provision of backup equipment, and price. For each lot, up to three candidates were recommended in rank order. If a firm had already been ranked first in two lots, it was excluded from further consideration, and the next-highest bidder was advanced.

In December 2015, the MEP released the official results of the tender (the bidder list, as is common in government procurement, was not released), with the names of the six firms and associated twelve lots, for O&M contracts covering 2016-2018.

The design of these outsourcing contracts was intended to address the risk of manipulation, which was well understood by central government bureaucrats. Since contracts covered monitoring stations across multiple provinces (and many prefectures), it was believed to be less likely that the winning firms could develop close ties with local officials that could later be exploited.[10] In

[9]With the exception of the four cities directly governed by the central government (Beijing, Shanghai, Tianjin, and Chongqing), as well as cities in Xinjiang, Gansu, Yunnan, Hainan, Guizhou, Ningxia, Fujian, Tibet, and Qinghai, all of the other cities in each provincial region were split into two lots.

[10]As Yi Luo, then Director of the Monitoring Department of the MEP, explained in an interview with *21st Century Business Herald* in August 2015, "after the central government took over authority for national monitoring stations, the China National Environmental Monitoring Center did not directly manage them but instead delegated operations to third-party firms through public tendering, precisely to reduce the risk of local govern-

addition, operating costs were fully covered by the MEP, rather than local governments, so that local governments did not pay monitors directly. However, these formal safeguards did not rule out the influence channels that we argue are suggested by the patterns we observe in the data, which operated through an implicit quid pro quo involving (local) government procurement contracts in other areas.[11]

2.2 Data Sources

2.2.1 O&M Firms Delegation

Our analysis focuses on the first round of O&M outsourcing, which has the benefit of capturing the direct transition at the end of 2015 from local government to third-party operation. The second round covered 2019-2021, which was affected by the COVID-19 pandemic. We did not collect data for this period, because the central government prioritized containing the spread of the virus at that time, leading to very different incentive structures for city leaders.

Using records from the China Government Procurement Database, maintained by China's Ministry of Finance, we obtained details of the contracts that the six designated O&M firms signed with the China National Environmental Monitoring Center, which is responsible for coordinating environmental monitoring within the Ministry of Environmental Protection.[12] These contracts provide information on the assignment of monitoring station operations to each firm across different cities.

Panel (b) of Figure 1 shows the geographical distribution of these assignments. Inherent to the procurement process, there is some clustering of

ment interference in reported data." See `https://m.21jingji.com/article/20150806/herald/5e92727524f639b7f2e949a2429feb94.html`, accessed September 30, 2025.

[11]It is natural to wonder why the central government did not subsequently restrict the six designated firms from bidding on procurement contracts in cities where they had O&M responsibilities. We know of no public discussion of this topic, but we can speculate that such restrictions may have dissuaded firms from bidding on the pollution monitoring contracts in the first place.

[12]Before 2024, the China Government Procurement Database allowed access to nearly all government contracts dating back to 2015. However, in 2024 the platform restricted public access to contracts to only the last three years. Our data were obtained before this change.

monitoring responsibilities for each O&M firm. But the clusters themselves are geographically dispersed. Moreover, we find that the prefecture characteristics of each of the six groups are statistically indistinguishable from one another. We show this for baseline (2015) characteristics including log Gross Regional Product (GRP) per capita, log population, industrial share value added, and various pollution measures (see Appendix Figure A2). While we cannot rule out the possibility of unobserved differences that are correlated with the assignments, all extant evidence suggests that they were not driven by regional or other specialization.

2.2.2 Local Government Procurement Contracts (2015-2018)

We obtained contract-level data on public contracts awarded by local Environmental Protection Bureaus (EPBs) at the prefecture or county level from the China Government Procurement Database.[13] We focus on contracts awarded to the six O&M firms delegated by the central government, and limit our data collection to EPBs which, given the business lines of the six firms, is the branch of government where they would almost exclusively be likely to seek procurement opportunities. In total, we obtained information on 431 procurement contracts between local governments and these six firms. These contracts themselves are generally for monitoring stations in less urban areas and in industrial zones within their jurisdiction. To meet these additional air quality monitoring responsibilities, local governments could establish their own monitoring stations or procure equipment and services from third-party firms to track both air and water pollution. For the sample of city-firm pairs with at least one contract between 2015 and 2018, we constructed a balanced panel at the city-firm-quarter level, resulting in 2,048 observations.[14]

[13] Counties are administrative sub-regions within cities.

[14] We conduct the analysis at the firm-city-quarter level in the main text rather than at the monthly level because the procurement data are sparse. For the same reason, we also adopt the quarterly frequency in our analysis of air pollution enforcement. In robustness checks, we collapse the data to the monthly level and obtain consistent results (see Appendix Table A1). Note that our results are also robust to including all city-firm-quarter observations, including pairs that never had a contract during the sample period (see Appendix Table A2).

2.2.3 Ground-based Reported Data and Satellite-based Data on Air Pollutants

For our measures of ground-based air pollution derived from monitoring stations, we use the website of the China National Environmental Monitoring Center, which reports hourly readings of six key air pollutants: sulfur dioxide (SO_2), nitrogen dioxide (NO_x), carbon monoxide (CO), particulate matter (PM_{10} and $PM_{2.5}$), ozone (O_3), and the overall air quality index (AQI) based on these pollutants. We focus on three main indicators in the analysis: $PM_{2.5}$, PM_{10}, and AQI, since regulatory targets place a particular emphasis on particulate matter concentrations and the composite AQI measure (Cao et al., 2025; Yang et al., 2024). The final dataset contains pollution readings from 1,472 monitoring stations, covering each hour from 2015 to 2018. For our empirical analysis, we aggregate the hourly data to the daily level by simply taking the daily average of each pollutant. (In Appendix A, we provide further details on the construction of our pollution dataset as well as additional information on the enforcement data.)

As a benchmark against which to compare these ground-based measures, we collect daily satellite-based data from the MERRA-2 reanalysis, produced by the NASA Global Modeling and Assimilation Office (Global Modeling and Assimilation Office , GMAO). MERRA-2 combines multiple satellite retrievals with atmospheric models to produce daily estimates of the mass densities of fine particulate matter, including dust, organic carbon, black carbon, sea salt, and sulfate. Following the specification in the GMAO document (Keller et al., 2021), we aggregate the MERRA-2 aerosol components to construct $PM_{2.5}$ concentrations, applying a molecular-weight adjustment for sulfate.[15] The dataset is available at an hourly frequency. For each ground monitoring station, we calculate the daily average satellite-based $PM_{2.5}$ concentration within a 10-kilometer radius.[16]

In Appendix Table A3, we study the correlation between satellite-based $PM_{2.5}$ and reported $PM_{2.5}$, as well as reported PM_{10} and AQI, controlling for station and day fixed effects. The estimated coefficient is around 0.3, which is

[15] Specifically, $PM_{2.5}$ is calculated as dust (DUSMASS25) + organic carbon (OCSMASS) + black carbon (BCSMASS) + sea salt (SSSMASS25) + sulfate (SO4SMASS) $\times$ (132.14/96.06).

[16] As a robustness check (see Appendix Table A4), we also use the satellite-derived surface $PM_{2.5}$ estimates from the Atmospheric Composition Analysis Group (ACAG), which offer finer spatial resolution but are available only at a monthly frequency.

very close to the findings in Axbard and Deng (2024), who use satellite-based Aerosol Optical Depth (AOD) as their proxy for pollution. This similarity is reassuring, as our measure is derived from an atmospheric reanalysis that assimilates AOD observations, and both approaches are designed to capture variation in particulate matter concentrations.

We also include city-level meteorological controls for our analysis from the same NASA GMAO dataset, including barometric pressure, humidity, wind speed, and surface temperature. Daily rainfall data are obtained from the Global Surface Summary of the Day dataset.

2.2.4 Polluters and Environmental Regulatory Enforcement by Local EPBs

For our analysis of environmental enforcement actions against polluters, we begin by determining the locations of industrial firms (along with financial information such as sales, profits, assets, and liabilities). We use the 2013 wave of the Annual Survey of Industrial Firms (ASIF), collected and maintained by the National Bureau of Statistics. The 2013 ASIF is the most recent survey prior to the 2016 reform that provides complete firm-level information, including firms' names, locations and detailed financials. The ASIF covers all state-owned industrial enterprises (SOEs) as well as private industrial firms with annual sales above RMB 20 million. We geocode the addresses of these enterprises using Gaode, a widely used Chinese digital map and navigation service, and calculate the distance from each enterprise to the nearest relevant air monitoring station.

We collect environmental enforcement data from PKU Law, which is a widely used platform that compiles laws, regulations, and enforcement decisions in China. For our analysis, we restrict the sample to cases enforced specifically by local (city or county) EPBs and match the penalized firms in these records to those in the ASIF, resulting in 37,784 matched cases. Using text recognition of penalty documents, we further distinguish between violations related to air pollution and other types of pollution. We then limit the sample to the period 2016–2018, yielding 9,543 penalties related to air pollution. Our analysis focuses on industrial firms that were subject to at least one environmental enforcement action during this period.[17]

[17]Focusing on these firms captures pollution-intensive businesses that are thus at genuine

2.2.5 City-Level Socioeconomic Data

City-level economic indicators are obtained from the China City Statistical Yearbook, an official annual publication series of the National Bureau of Statistics that provides comprehensive data on local economic and demographic conditions.

Summary statistics for variables from each of the three datasets we use in our analysis are in Appendix Table A5. Panel (a) summarizes transactions between local governments and the O&M firms in our sample. Importantly, these contracts cover all types of procurement with these firms and are not restricted to the monitoring-station O&M contracts that form the basis of our identification. The data reveal that transactions are sparse: only about 14 percent of city–firm–quarter observations involve any contract, and the median contract value is zero, although a small number of large contracts generate a highly skewed distribution. The average distance between a city and the firm's headquarters is over 770 kilometers, suggesting that procurement relationships are not confined to local markets. Panel (b) reports pollution levels from both national monitoring stations and satellite-based measures. We find that the reported means of $PM_{2.5}$, PM_{10}, and AQI for 2016–2018 are very close to those reported in Axbard and Deng (2024), who examine data from 2015-2017. The standard deviations in our sample are larger, which is expected since we use daily averages whereas their analysis is based on monthly averages. Panel (c) shows enforcement outcomes at the polluter-quarter level. $Enforcement$ is an indicator equal to one if the polluter received any enforcement action targeting air pollution, while $Enforcement_{other}$ refers to enforcement actions related to other types of pollution (such as water, soil, or noise pollution). We see that enforcement is relatively infrequent: on average, about 3% of polluter–quarters experience at least one enforcement action related to air pollution, and about 7% experience enforcement related to other types of pollution. Moreover, around 40% of the polluters in our sample are located within 15 km of a monitoring station, suggesting that the sitting of monitoring stations was not random, a point we return to below. Consistent with this, additional evidence in both Appendix Table A6 and Appendix Figure A3 indicates that national monitoring stations tend to be located closer to larger and more-polluting plants.

risk of regulatory scrutiny – most firms face little such risk.

Appendix Table A7 compares cities with and without related procurement across the three datasets. Panel (a) shows that, whether we use reported or satellite-based data, cities with related procurement exhibit higher levels of pollution during 2016–2018. We find this to be an interesting pattern, as the more-polluted cities would have a greater incentive to bring down reported pollution. Panel (b) shows that cities with related procurement have a higher probability of air-pollution-related enforcement actions (3.9% vs. 2.9%) but a slightly lower probability of enforcement related to other pollutants (6.6% vs. 7.4%). In terms of firm distribution, 39% of polluters in "related procurement" cities are located within 15 km of a monitoring station compared with 44% in other cities, while the shares at 15-30 km and 30-45 km are correspondingly higher. Finally, Panel (c) examines city-level characteristics in 2015. While GRP per capita, growth, and industrial composition are similar across groups, cities with related procurement are larger in population size and record significantly higher emissions of NO_x and SO_2. Overall, the two groups of cities do not differ substantially in terms of economic level or industrial structure, but they differ in pollution intensity. Cities with higher pollution levels, which may have the greatest need to reduce emissions, are also somewhat more likely to engage in related procurement.

3 Results

Before proceeding to the core analysis on pollution monitoring reforms, related procurement, and observed pollution, we begin by showing the time-series patterns in $PM_{2.5}$ concentration, both as measured by ground-based monitoring stations and also satellite images. For each city, we take the worst air pollution reading in a given month, to reflect the political salience of "red alert" pollution days and severe pollution in general (Ghanem and Zhang, 2014).[18] Because there is such strong seasonality and location-specificity to the extent of pollution, we also partial out month and city effects.

[18]See, e.g., "When the ranking is low, the data must be lowered," *The Paper* (`https://www.thepaper.cn/newsDetail_forward_1967703`, January 25, 2018. Last accessed on September 30, 2025). Local environmental officials in this case had access to a real-time monitoring app that displayed the jurisdiction's air quality index and its ranking. When their jurisdiction ranked poorly, officials reportedly sought ways to lower the reported readings of national monitoring stations.

We provide the resultant plot in Figure 2, with three-month moving averages in darker lines, and less prominent markers with 90% confidence intervals for the monthly data. There are several noteworthy patterns. First, there is a substantial drop in both ground-based and satellite-based $PM_{2.5}$ measurements that coincides with the new law at the end of 2015. Curiously, the satellite-based measures drop in late 2015, two months before the outsourcing regime is put in place, while ground-based measures do not decline until the very beginning of 2016. One plausible interpretation is that, when the tender for outsourcing contracts was announced in the fourth quarter of 2015, cities refrained from manipulating air pollution measures, while also taking steps to reduce actual pollution.

Of greater relevance from our perspective, while satellite-based measures of air pollution subsequently remained stable, data from ground-based monitoring show a secular decline in measured pollution throughout our sample period. Our focus will be on understanding why, despite the fact that satellite-based measures – which could not be manipulated by local governments – remained fixed after reforms were implemented, air pollution measured on the ground continued to decline.

The main thesis of this paper is that a form of implicit collusion accounts for this pattern, with city governments awarding procurement contracts to firms assigned O&M responsibilities, and these firms then manipulating monitoring station measurements to show reduced air pollution.

The empirical analysis that follows proceeds in several steps. We first show that there was a relative increase in "related" procurement contracts assigned after the outsourcing reform, in line with the first part of the argument above. We then show that ground-based air pollution as measured by monitoring stations went down immediately following the signing of these contracts, while we observe no change in satellite-based air pollution measures. Using these two sets of results, we can then make a back-of-the-envelope calculation to estimate the extent to which related procurement accounts for the post-reform drop in measured air pollution. Given that leaders' incentives force them to confront a trade-off between environmental quality and industrial output, it is then natural to ask whether there was any impact of related contracting on air pollution enforcement actions, which we provide in our final set of main analyses. We then conclude by presenting a series of robustness and heterogeneity analyses to more persuasively tie our main results to our favored explanation based on favor-exchange, and to probe the sensitivity of our results to different empirical assumptions.

3.1 Outsourcing reform and Related Procurement

To identify a potential relationship between outsourcing reform and "related" procurement, we estimate the following specification:

$$\begin{aligned} AnyContract_{c,f,q} = \; & \beta \cdot Related_{c,f} \cdot Post2016_q \\ & + \delta_{c,f} + \theta_q + \mu_{c,y} + \nu_{f,y} + \lambda_c q + \kappa_f q + \epsilon_{c,f,q} \end{aligned} \quad (1)$$

where $AnyContract_{c,f,q}$ denotes whether there is at least one procurement contract that had been signed between firm f and city c in quarter q, where the set of potential firms receiving procurement contracts is the six companies with O&M responsibilities following the reform. $Post2016_q$ denotes quarters during 2016-2018 (i.e., post-reform), while $Related_{c,f}$ denotes that firm f has O&M responsibility for air pollution monitoring in city c. In this difference-in-differences framework, our main hypothesis is that, post-reform, there is a relative increase in the proportion of related procurement contracts signed by city governments, i.e., $\beta > 0$. The sample includes all city-firm pairs for which there was at least one procurement contract signed during our sample period.

This specification absorbs a range of confounding factors that may otherwise bias β's interpretation. By including for city-firm pair fixed effects $\delta_{c,f}$, we absorb all time-invariant differences in procurement propensity across pairs. Including year-quarter fixed effects θ_q controls for macro-level shocks or seasonal patterns that affect all firms and cities uniformly. The inclusion of city-by-year fixed effects $\mu_{c,y}$ and firm-by-year fixed effects $\nu_{f,y}$ controls flexibly for time-varying heterogeneity across cities and firms, such as local budget cycles or firm-specific strategic shifts. Finally, controlling for city-specific linear trends $\lambda_c q$ and firm-specific linear trends $\kappa_f q$ helps capture gradual shifts in procurement behavior unrelated to the reform. We cluster standard errors at the city-firm pair level, given that we view this as the appropriate level of "assignment" of the related "treatment" (in practice our results are near-identical if we use city-level clustering). Our basic identifying assumption is that there are no other concurrent policy changes that would differentially impact a subset of firm-city pairs in such a way as to increase related procurement.[19]

[19] Given that this test exploits a one-time policy shock rather than staggered adoption,

We present our main regression results in Table 1, which focuses on the extensive margin of related contract procurement. Given the relative sparseness of municipal and county procurement contracts won by the six firms in our sample, this is our favored approach to capturing the relationship. In column (1), where no fixed effects are included, our estimate of $\hat{\beta}$ is 0.104, statistically significant at the 1% level. Given the baseline (2015) value of $AnyContract$ in our data of 0.125, this implies an increase of 83%. The negative coefficient on *Related* further suggests that before the reform, related firms were actually somewhat less likely to transact than their counterparts. Column (2) adds city-firm pair and year-quarter fixed effects, absorbing time-invariant pair characteristics and common time shocks. The coefficient on the interaction term remains essentially unchanged at 0.104, which shows that the effect is not driven by baseline differences between pairs or aggregate time trends. In column (3), we include city-year and firm-year fixed effects to control for differential shocks at both the city and firm level. In this specification the coefficient on $Related \times Post2016$ increases to 0.166. Finally, our favored coefficient in column (4) incorporates city-by-quarter and firm-by-quarter trends. The coefficient on the interaction term remains positive and significant, and its magnitude is very similar to that of column (3).

We provide a series of basic robustness checks on our main results. In Appendix Table A8, we present results that consider potential intensive margin effects, using as the dependent variable either the number or value of contracts. Whether we use a linear specification or Poisson pseudo-maximum likelihood (PPML) to address potential concerns about log-transforming zero values, we obtain point estimates that are in line with the results reported above. Appendix Table A2 includes city-firm pairs even if they never transacted during our sample period, and Appendix Table A1 collapses our dataset to the pair-month level; we again obtain results that are in line with those reported in Table 1.

Overall, our results thus far indicate a very sizable increase in local government procurement contracts awarded to firms responsible for operating their air quality monitoring stations after the implementation of outsourcing reforms. To explore the dynamics around the reform date – and to assess whether the observed changes in related outsourcing coincide with the reform

we do not face the concerns about heterogeneous treatment timing in DiD designs.

date – we estimate an event study specification of the form:

$$\begin{aligned} AnyContract_{c,f,q} = &\sum \beta_k \, Related_{c,f} \cdot Quarter_k \\ &+ \delta_{c,f} + \theta_q + \mu_{c,y} + \nu_{f,y} + \lambda_c q + \kappa_f q + \varepsilon_{c,f,q} \end{aligned} \tag{2}$$

The model is similar to that of Equation (1), but allows the likelihood of a related firm winning a procurement contract to vary dynamically, relative to the baseline quarter (2015Q4).

Figure 3 presents these results. The estimated coefficients are close to zero prior to 2016, supporting the parallel trends assumption. Post-reform, the coefficients increase sharply and largely remain positive throughout the post-reform period, without any clear pattern of reversion.

3.2 Related procurement and measured air pollution

The next step in our argument is to link procurement contracts signed by cities with the firm managing their monitoring stations to subsequent changes in air pollution measured by these monitoring facilities. We construct a variable, $PostProcure_{c,m}$, which denotes whether city c had signed a procurement contract with the firm with O&M responsibilities for its monitoring stations, by month m. (As we noted earlier there are relatively few instances of multiple procurement contracts between a city and the firm with O&M responsibilities, so this is similar in practice to a variable that captures the number of such contracts.)

Using daily monitoring station data from the entire post-period of 2016-2018, we then estimate the following specification:

$$\begin{aligned} \log(Pollution)_{s,d} = &\, \beta \, PostProcure_{c,m} + \Gamma CV_{c,d} \\ &+ \delta_s + \zeta_d + \theta_{p,q} + \kappa_{f,q} + \lambda_c m + \epsilon_{s,d} \end{aligned} \tag{3}$$

The outcome variable $Pollution_{s,d}$ is a measure of air pollutants reported by monitoring station s on day d. We focus on three key indicators: $PM_{2.5}$, PM_{10}, and AQI, which are the main metrics used in official environmental performance assessments of local governments (Cao et al., 2025; Yang et al., 2024). We use log values for all pollution measures because of the presence of a small number of extreme short-term readings in particulate matter concentrations. For instance, the 99.5th percentile of $PM_{2.5}$ is 220, yet there are

2 observations above 2000. The vector of controls $CV_{c,d}$ includes city-by-day-level meteorological variables, such as surface pressure, humidity, wind speed, and surface temperature, which may directly affect measured pollutant concentrations. We also include a rich set of fixed effects.[20] Monitoring station fixed effects δ_s absorb time-invariant differences across stations, such as geographic location, elevation, and local infrastructure. Day fixed effects ζ_d capture nationwide shocks or time-specific factors, such as national holidays, extreme weather events, or seasonal pollution trends. Province-by-quarter fixed effects $\theta_{p,q}$ control for time-varying shocks that are common across all cities within the same province, such as province-level regulatory campaigns or weather anomalies. Firm-by-quarter fixed effects $\kappa_{f,q}$ account for time-varying factors at the firm level, including strategic behavior or other contractual obligations that might influence pollution data reporting. Finally, city-specific linear monthly trends $\lambda_c m$ capture gradual changes in pollution levels at the city level that may be unrelated to the outsourcing reform, such as long-term infrastructure improvements or economic trends. The error term $\epsilon_{s,d}$ is clustered at the city level to allow for arbitrary correlation in pollution measurements within a city over time.

Pollution measured at ground-level monitoring stations captures a combination of actual changes in pollution as well as any possible manipulation. As a benchmark, or a placebo test of sorts, we use satellite-based measurements of air pollution, based on the same specification above. Specifically, we use satellite-derived $PM_{2.5}$ measurements averaged within a 10-kilometer radius of each station. If our satellite-based pollution measure is unaffected by related procurement, it suggests that the reduction in reported pollution may be driven by manipulation.

We present these results in Table 2. In the first three columns, we present results for ground-based measures of (the logarithmm of) $PM_{2.5}$, PM_{10}, and AQI. Across all three measures, the coefficient on $PostProcure$ is negative and significant at least at the 5% level. All values can be roughly interpreted as elasticities, so the decline in measured pollution is between 3.3 and 5%.

In column (4) we use a $PM_{2.5}$ proxy based on satellite data. As noted earlier, this remote-sensing measure is not subject to manipulation by local

[20]We also consider specifications with alternative fixed effects to examine the impact of related contracting on both reported $PM_{2.5}$ and satellite-based $PM_{2.5}$ (see Appendix Table A9). Except for columns (1) and (2) in Panel (a), where the magnitudes are somewhat smaller (though still significant at the 10% level), the results are largely consistent.

actors, and thus reflects actual pollution in the 10 kilometer radius around a monitoring station. In contrast to the results using ground data, we observe no significant change in satellite-based air pollution measures after the signing of a related procurement contract.[21] Finally, in column (5) we use the difference between ground- and satellite-based measures of $PM_{2.5}$ as a proxy for manipulation – as expected, given the patterns in columns (1) and (4), the coefficient on $PostProcure$ is negative and of approximately the same magnitude as in column (1).

Our findings in this section indicate that the drop in reported air pollution is the result of reported rather than actual improvements in air quality. We see these results as supporting the interpretation of the rise in related procurement as reflecting a collusive arrangement between the prefecture and monitoring firms – favorable air pollution measurement in exchange for contracts.

To further explore how the signing of related contracts affects pollution over time, we present an event plot, using average monthly pollution, to show the dynamics around the first instance of related procurement for each city. Specifically, our estimating equation is:

$$log(Pollution_{s,m}) = \sum_{k=-9}^{k=9} \beta_k * D^k_{c,m} + \delta_s + \zeta_d + \theta_{p,q} + \kappa_{f,q} + \lambda_c m + \epsilon_{s,d} \quad (4)$$

where D^k is the number of months before/after the first month that a procurement contract is signed between a city and the firm with O&M responsibilities. (As is standard, $D^k = 0$ for all observations in "never-treated" cities that do not have any such contracts.)

We show the resulting event plot under this two-way fixed effects (TWFE) specification in Figure 4, which shows the estimated coefficients for both ground-based reported $PM_{2.5}$ concentrations (in blue circles) and satellite-based $PM_{2.5}$ (in red diamonds). Prior to the signing of a related procurement contract, the two pollution measures show little difference. However, immediately after the first related procurement contract is signed, there is a discernible decline in ground-based $PM_{2.5}$ measures, while satellite-based

[21] We observe essentially the same pattern for an alternative (ACAG) method of using satellite data to measure $PM_{2.5}$ in Appendix Table A4 where we use a station-month panel in our estimation, and similarly observe no significant coefficient on $PostProcure$.

measurements remains stable. This divergence persists in the months that follow.

In contrast to our results on the link between reform and related procurement – which are identified based on a policy change at a single point in time – the preceding results are subject to the recent critiques of staggered difference-in-differences (see Roth et al., 2023 for a summary). To address potential concerns about heterogeneous treatment effects, in addition to our TWFE estimator, we also use several of the alternative estimators that have been proposed, specifically those of Cengiz et al. (2019); Callaway and Sant'Anna (2021); and Sun and Abraham (2021).

These results appear in Figure Appendix Figure A4, panel (a). The patterns are generally consistent across estimators – both the stacked DiD results (Cengiz et al., 2019) and those of Sun and Abraham (2021) are very similar to the TWFE estimates, indicating a drop in measured pollution that coincides with the signing of a related contract. While the estimates based on Callaway and Sant'Anna (2021) are less precise and somewhat attenuated relative to the other estimates, they are directionally consistent with a post-procurement reduction in measured pollution. In panel (b) we present the analogous estimates, but using satellite-based measures of $PM_{2.5}$. In contrast to the patterns in panel (a), satellite-based measurements show no change around the signing of related procurement contracts.

We conclude this subsection with a distinct set of concerns related to endogenous contracting. We have argued that related procurement contracts are awarded precisely because they create the expectation (potentially implicit) that O&M firms will then provide favorable air pollution measurements. Indeed, we view this endogeneity as the key result in our first set of analyses in Section 3.1.

We believe that, to the extent that this endogeneity concern biases the estimates in this subsection, the bias is toward zero. The reason is that the most likely source of endogeneity is that local governments will be more likely to sign procurement contracts with O&M firms that have already shown a willingness or ability to report lower air pollution numbers. This would lead to the signing of related procurement contracts if pre-period air pollution measurements are very low, so that the post-minus-pre difference would be mechanically attenuated.

If this were a common practice, we would expect to see a decline in measured air pollution in anticipation of the signing of a related procurement contract. However, we do not observe any such pattern in the event plots presented above.

We may use the estimates from this section to approximate the extent to which the decrease in measured air pollution following reform may be attributed to related contracting. We observe in Figure 2 that reported $PM_{2.5}$ exhibits a secular decline beginning in November 2017 relative to satellite-based measures. To gauge the overall decline, over the following twelve months, we calculate, for each monitoring station, the monthly average of $log(PM_{2.5})$ for November 2017 and for October 2018. We then difference these values and take the mean. This yields an average overall decline of about 4.2%. Using the robust treatment effect estimator of (Sun and Abraham, 2021), we estimate that related procurement reduces reported $PM_{2.5}$ by about 6.1%. In our sample, related procurement contracts were signed in approximately 13% of cities. A simple back-of-the-envelope calculation therefore implies that this mechanism accounts for roughly 19% (13%∗6.1%/4.2%) of the observed national decline in reported $PM_{2.5}$ over this period.

3.3 The real consequences of pollution under-reported

As discussed previously, prefectural leaders face a multitasking problem: they are evaluated based on both economic performance and environmental indicators. The capture of O&M firms may allow officials to improve industrial output by reducing the need for rigorous enforcement of air pollution, since observed air pollution can be reduced without requiring tightened enforcement.

In this subsection, we therefore examine how the intensity of enforcement is affected by related contracting. To do so, we constructed a firm-by-quarter panel from 2016 to 2018 using data from the 2013 Annual Survey of Industrial Firms combined with enforcement records issued by local EPBs. By matching polluting firms to their nearest monitoring stations, we can exploit within city-by-quarter variation in enforcement behavior before versus after the signing of a related procurement contract.

Following Axbard and Deng (2024), we consider a plant to be a relevant polluter for its nearest monitoring station if it is within 15 kilometers of it, which is denoted by the indicator variable, $I(Distance \leq 15km)$, where

$Distance$ captures the distance of firm f to the nearest monitoring station. Similar to Fisman et al. (2025), we use as a placebo firms between 30 and 45 kilometers away from the nearest monitoring station. This "donut hole" approach allows for sufficient distance between monitoring station and firm that its emissions are very unlikely to be relevant, but close enough that its characteristics (and more importantly, any trends in characteristics) may be more comparable to the nearby firms (though this is a point we return to below).

Specifically, we estimate the following:

$$\begin{aligned} AnyEnforcement_{f,q} = {} & \beta \, PostProcure_{c,q} \times I(Distance_f \leq 15 \text{ km}) \\ & + \delta_f + \theta_{c,q} + \kappa_{i,q} + \gamma_q \times \log(Assets)_{f,2013} \\ & + \gamma_q \times Lev_{f,2013} + \gamma_q \times ROA_{f,2013} + \varepsilon_{f,q} \end{aligned} \tag{5}$$

where $AnyEnforcement_{f,q}$ is a binary indicator equal to one if firm f received any environmental penalty from local regulators in quarter q, and zero otherwise. As before, the variable $PostProcure_{c,q}$ denotes whether city c has signed a procurement contract with its O&M firm by quarter q. We include city-by-quarter fixed effects, $theta_{c,q}$, so that identification comes from comparing polluters within the same city and quarter that differ in their distance to the nearest monitoring station. $\kappa_{i,q}$ are 2-digit industry-by-quarter fixed effects, which absorb industry-specific seasonal patterns that could drive enforcement differences. We also include firm characteristics from the baseline year of 2013, interacted with fixed effects.Lev is defined as liabilities divided by assets. ROA is defined as earnings before taxes divided by assets. Interacting these characteristics with quarter fixed effects (γ_q) controls for systematic differences in enforcement intensity across firms of different scale, capital structure, or profitability over time, ensuring that identification comes from within-group variation among firms with comparable financial conditions in the same quarter.

We present these results in Table 3, beginning in column (1) with a specification that does not include city-by-quarter fixed effects. This omission allows us to identify the direct effect of $PostProcure_{c,q}$. Since the benchmark is firms located 30-45 kilometers from the nearest station, in this expression $PostProcure_{c,q}$ identifies the change in air pollution enforcement for firms that are sufficiently distant from any monitoring station as to not affect air pollution measurements. Interestingly, this coefficient is positive and significant at the 10% level, indicating an *increase* in enforcement among firms more distant from monitoring stations. The size of the coefficient is large – relative to the pre-event mean of $AnyEnforcement$ of 0.029, the coefficient of 0.018 implies an increase in enforcement actions of over 44%. Our coefficient of primary interest, on the term $PostProcure_{c,q} \times I(Distance_f \leq 15km)$, is -0.022 (significant at the 5% level), indicating, if anything, a reduction in enforcement for firms closer to monitoring stations.

Broadly speaking, this suggests a substitution for enforcement away from nearby monitoring stations toward more distant ones. To interpret this intriguing result, it is important to note that the placement of monitoring stations may itself be endogenous. Establishments located within 15 kilometers of a monitoring station have, on average, nearly twice the asset size of those located 30-45 kilometers away, and their NO_x emissions are about 1.5 times higher (see Appendix Table A6 and Appendix Figure A3). These patterns suggest that monitoring stations were located near to larger and more polluting firms.

A natural interpretation of the results in column (1) is thus that manipulation of monitoring station pollution measurements may have facilitated the substitution of enforcement efforts away from targets that were responsible for higher emissions (as well as higher economic output), toward less consequential (from an economic output perspective) companies.

We note that all specifications – including that of column (1) – include firm fixed effects as well as size-by-time fixed effects, so that these results are not simply picking up differential impacts on larger versus smaller firms. As a separate approach to probing these concerns, we generate event plots based on specifications similar to that of column (1), but estimated separately for nearby (less than 15 kilometers) and more distant (30-45 kilometers) firms. The resulting patterns are shown in Figure 5, which shows that the two groups followed very similar trends prior to the signing of a related procurement contract, and only then do they diverge.

In columns (2)-(4) we present a series of further specifications to probe the robustness of the main result linking related procurement to a relative reduction in enforcement actions against nearby firms. Column (2) simply repeats the specification from the first column, adding city-by-quarter fixed effects to pick up any city-wide shifts in enforcement. We observe a point estimate on $PostProcure_{c,q} \times I(Distance_f \leq 15km)$ that is slightly higher than that of the first column. In columns (3) and (4) we consider smaller (less than 10 kilometers) and larger (less than 20 kilometers) radii to define nearby establishments. The results are largely insensitive to the particular choice of cutoff, though it is notable that, the point estimate is slightly larger in magnitude for the smaller radius. Finally, in column (5) we present a further placebo test, examining enforcement actions related to other types of pollution (most commonly water, noise, and soil). We find no evidence of an impact of related procurement on these nearby enforcement actions, suggesting that our results are specific to air pollution.

3.4 Heterogeneity, robustness, and extensions

3.4.1 Promotion incentives, related contracting, and measured air pollution

As discussed earlier, the main motivation for reducing measured air pollution is that it is an input into local leaders' promotion. Therefore, the phenomenon we explore should be less prominent for "term-limited" leaders, who are not eligible to be promoted. To do so, we follow Axbard and Deng (2024), who identify politician time horizon based on two features of China's political institutions. First, city-level officials are nearly three times more likely to be promoted in the final year of China's five-year political cycle (Xi, Yao and Zhang, 2018), which coincides with the convening of the NPC. Second, there is a norm that prefecture-level officials are unlikely to be promoted if they are older than 57. This age threshold leads to a sharp drop in promotion prospects, implying significantly weaker political incentives for those above that age (Huang et al., 2024).

To implement this heterogeneity test, we collected the age of each city's party secretary. This information comes primarily from the CCER Official Dataset (Yao et al., 2022), which we supplement with other public records at the time of the 13th NPC held in March 2018.[22] If political incentives are an

[22]For the period 2015-2017, information on cities' party secretaries is obtained from the CCER official database. For 2018, we collect the data manually, since the CCER database only provides information up to 2017. We use provincial yearbooks to identify party secretaries' names and then search for their official resumes to extract personal characteristics and career trajectories. The primary online sources are government websites and Baidu Baike (`http://baike.baidu.com/`), a widely used Chinese online encyclopedia similar to Wikipedia. We use the age of the city's party secretary rather than the mayor. In the Chinese political hierarchy, the party secretary is the top decision-maker with ultimate

important factor in explaining the observed increase in related procurement following the outsourcing reform, we expect to see a more pronounced increase in cities where the party secretary was 57 or younger during the 2018 NPC.

Specifically, we estimate the following triple-differences specification:

$$\begin{aligned} AnyContract_{c,f,q} = {} & \beta\, Related_{c,f} \times Post2016_q \times I(Age \leq 57)_{c,y} \\ & + \alpha\, Related_{c,f} \times Post2016_q + \gamma\, Related_{c,f} \times I(Age \leq 57)_{c,y} \\ & + \delta_{c,f} + \theta_q + \mu_{c,y} + \nu_{f,y} + \lambda_c q + \kappa_f q + \varepsilon_{c,f,q} \end{aligned} \tag{6}$$

The estimating equation here is very similar to that of Equation (1), but augmented with a third-order term that includes the interaction of $Related_{c,f} * Post2016_q$ with $I(Age \leq 57)_{c,y}$, an indicator variable denoting cities where the party secretary was 57 or younger in 2018. We present the results in Appendix Table A10, using specifications that exactly parallel those of Table 1. Columns (1)-(3) use the full sample of cities, and columns (4)-(6) repeat the analysis after excluding the four centrally administered municipalities (Beijing, Shanghai, Tianjin, and Chongqing), since party secretaries in these cities face a retirement age of 65 rather than 60, making our age-based cutoff less applicable. In both sets of results, the coefficient on the triple-interaction term is generally positive and statistically significant, indicating that the effect we document in our main results is more prominent for leaders with concerns over future promotion. Notably, the results in Columns (4)-(6) are notably larger than those in columns (1)-(3), suggesting that the main effects are indeed driven by cities where the party secretary was 57 or younger (and thus still eligible for promotion).

Focusing on our main outcome variable, $AnyContract$, we allow for greater flexibility in the relationship between age and related contracting by repeating the analysis in Equation (6), using a series of indicator variables for the ages of party secretaries during the 2018 NPC. The coefficients on the relevant third-order terms as well as their 90% confidence intervals appear in Figure 6. The pattern clearly illustrates that the promotion incentive result is driven largely by those approaching – but not yet at – retirement age. The sharp drop-off between 57 and 58 suggests in particular that promotion

authority over major policy issues, including environmental regulation, and thus more directly accountable in cadre evaluations, while the mayor primarily plays an executive role.

incentives plausibly play an important role in the phenomenon we document in our main results.

3.4.2 Could reduced information frictions have increased related contracting?

An alternative interpretation for our results linking O&M responsibility to subsequent procurement contracts is that the former simply reduced information frictions such that, all else equal, after reform a related firm is more likely to win additional government contracts. We note two things. First and foremost, we emphasize that this information-based explanation cannot explain why we observe a drop in reported pollution post reform while satellite-based pollution data remain unchanged. Second, if this were the case it offers a distinct but closely related interpretation of our pollution results – the reduced information frictions that lead to increased related procurement contracts may also facilitate the collusive government-firm relationships that allow for downward manipulation of air pollution measurements.

While we cannot rule out this latter interpretation – which would be interesting in its own right – several patterns in the data lead us to believe that it is less likely to explain the post-reform shifts we observe. Most importantly, we observe a sharp and discontinuous shift in the likelihood of related procurement that coincides with the reform date. The development of mutual understanding would, we argue, tend to appear more gradually over time, so that we would have expected a more gradual increase in the post-reform period in Figure 3. Second, if we presume that initial information frictions are correlated with proximity between a firm and city pair, those closer together initially should see a larger impact from an O&M relationship (under the assumption of substitutability between these sources of connections). Yet we do not observe any mediating effect of distance between a city and O&M firm headquarters on post-reform related contracting (see Appendix Table A11). While neither of these tests is decisive, together they provide suggestive evidence that reduced information frictions is less likely the cause of the patterns we observe in our main results.

3.4.3 Weather shocks and reported substitution

In this section, we explore how rainfall impacted air pollution measurements recorded by monitoring stations. Since precipitation causes particulate matter to settle and thus lower recorded pollution, we expect that in wetter periods, the link between related procurement and air pollution as measured by monitoring stations should be attenuated. This effect is plausibly reinforced by the means through which, by many accounts, measured air pollution is manipulated. It is unlikely that intervention comes through direct alteration of data, since monitoring stations operated autonomously. Rather, a widely suspected strategy was to artificially reduce pollution concentrations around monitoring sites by spraying water into the air which, similar to rainfall, causes lower recorded pollution.

To test this hypothesis, we define a variable, $Rainfall$, that is the average daily rainfall in a given city-quarter. We then augment our baseline specification from Equation (3) with the interaction of $PostProcure \times Rainfall$ to capture the differential impact of rainfall on measured pollution after the signing of a related procurement contract. We present these results in Table 4 for each of the three main pollution measures ($Log(\mathrm{PM}_{2.5})$, $Log(\mathrm{PM}_{10})$, and $Log(AQI)$). Focusing first on the direct effect of $Rainfall$, the coefficient is positive, as expected given that precipitation tends to reduce air pollution. Of greater interest, this link is much attenuated after a related procurement contract is signed, suggesting that the city may have substitute mechanisms (like spraying water themselves) to reduce measured pollution.

4 Conclusion

Third-party monitoring is a common solution to principal-agent problems in organizations, both public and private. In this paper, we show that this solution is at least partly undermined by endogenous responses by the monitored party to influence an ostensibly independent monitor. Specifically, we show that following a 2015 reform that shifted the operation of national air pollution monitoring stations from local governments to independent O&M firms, many local governments quickly signed procurement deals with these firms. These transactions may have effectively acted as a form of implicit collusion: in exchange for local business opportunities, the firms were motivated to help local officials present more favorable environmental data. As a result, measured air pollution declined, but it was not accompanied by real declines (as captured by satellite-based measures). We further show that there were real consequences of manipulation, with fewer enforcement actions taken against (large and relatively high-polluting) firms situated near monitoring stations.

We conclude with two observations. First, because the reform occurred at a single point in time, it is difficult to identify whether the shift in monitoring responsibility led in aggregate to a decline in air pollution – pollution declined in general in the period we study, so we cannot isolate any specific role of the policy overall. We highlight one feature of the policy that limited its efficacy, rather than making a statement about the reform's net impact. Second, our findings emphasize the importance of designing monitoring systems to limit capture of the sort we document. The contracts governing O&M relationships could have, for example, restricted subsequent related procurement contracts between local governments and assigned O&M firms – though this restriction may in turn have impacted the set of bidders for O&M contracts. How to optimally manage this nexus of tradeoffs is a larger question that we hope to address in future research.

References

Asunka, Joseph, Sarah Brierley, Miriam Golden, Eric Kramon, and George Ofosu. 2019. "Electoral fraud or violence: The effect of observers on party manipulation strategies." *British Journal of Political Science*, 49(1): 129–151.

Axbard, Sebastian, and Zichen Deng. 2024. "Informed Enforcement: Lessons from Pollution Monitoring in China." *American Economic Journal: Applied Economics*, 16(1): 213–52.

Barnwal, Prabhat. 2024. "Curbing leakage in public programs: Evidence from India's direct benefit transfer policy." *American Economic Review*, 114(12): 3812–3846.

Barwick, Panle Jia, Shanjun Li, Liguo Lin, and Eric Yongchen Zou. 2024. "From Fog to Smog: The Value of Pollution Information." *American Economic Review*, 114(5): 1338–81.

Bertrand, Marianne, Matilde Bombardini, and Francesco Trebbi. 2014. "Is It Whom You Know or What You Know? An Empirical Assessment of the Lobbying Process." *American Economic Review*, 104(12): 3885–3920.

Blanes i Vidal, Jordi, Mirko Draca, and Christian Fons-Rosen. 2012. "Revolving Door Lobbyists." *American Economic Review*, 102(7): 3731–48.

Buntaine, Mark T., Michael Greenstone, Guojun He, Mengdi Liu, Shaoda Wang, and Bing Zhang. 2024. "Does the Squeaky Wheel Get More Grease? The Direct and Indirect Effects of Citizen Participation on Environmental Governance in China." *American Economic Review*, 114(3): 815–50.

Callaway, Brantly, and Pedro HC Sant'Anna. 2021. "Difference-in-differences with multiple time periods." *Journal of econometrics*, 225(2): 200–230.

Cao, Guangyu, Xi Weng, Mingwei Xu, and Li-An Zhou. 2025. "The political economy of ratchet effect: Evidence from China's environmental regulation." *Journal of Environmental Economics and Management*, 131: 103150.

Causholli, Monika, Dennis J. Chambers, and Jeff L. Payne. 2014. "Future Nonaudit Service Fees and Audit Quality." *Contemporary Accounting Research*, 31(3): 681–712.

Cengiz, Doruk, Arindrajit Dube, Attila Lindner, and Ben Zipperer. 2019. "The Effect of Minimum Wages on Low-Wage Jobs*." *The Quarterly Journal of Economics*, 134(3): 1405–1454.

Chang, Eric C. C., Miriam A. Golden, and Seth J. Hill. 2010. "Legislative Malfeasance and Political Accountability." *World Politics*, 62(2): 177–220.

Chen, Yvonne Jie, Pei Li, and Yi Lu. 2018. "Career concerns and multitasking local bureaucrats: Evidence of a target-based performance evaluation system in China." *Journal of Development Economics*, 133: 84–101.

Chu, Jian, Raymond Fisman, Songtao Tan, and Yongxiang Wang. 2021. "Hometown Ties and the Quality of Government Monitoring: Evidence from Rotation of Chinese Auditors." *American Economic Journal: Applied Economics*, 13(3): 176–201.

Di Tella, Rafael, and Ignacio Franceschelli. 2011. "Government Advertising and Media Coverage of Corruption Scandals." *American Economic Journal: Applied Economics*, 3(4): 119–51.

Duflo, Esther, Michael Greenstone, Rohini Pande, and Nicholas Ryan. 2013. "Truth-telling by Third-party Auditors and the Response of Polluting Firms: Experimental Evidence from India*." *The Quarterly Journal of Economics*, 128(4): 1499–1545.

Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, Guojun He, and Maigeng Zhou. 2017. "New evidence on the impact of sustained exposure to air pollution on life expectancy from China's Huai River Policy." *Proceedings of the National Academy of Sciences*, 114(39): 10384–10389.

Faccio, Mara. 2006. "Politically Connected Firms." *American Economic Review*, 96(1): 369–386.

Fisman, Raymond, Pulak Ghosh, Arkodipta Sarkar, and Jian Zhang. 2025. "Dirty air and green investments: The impact of pollution information on portfolio allocations." National Bureau of Economic Research.

Ghanem, Dalia, and Junjie Zhang. 2014. "'Effortless Perfection:' Do Chinese cities manipulate air pollution data?" *Journal of Environmental Economics and Management*, 68(2): 203–225.

Global Modeling and Assimilation Office (GMAO). 2015. "MERRA-2 tavgM_2d_aer_Nx: 2d, Monthly mean, Time-averaged, Single-Level, Assimilation, Aerosol Diagnostics V5.12.4." *Goddard Earth Sciences Data and Information Services Center (GES DISC), Greenbelt, MD, USA*, Accessed: [Data Access Date].

Greenstone, Michael, and Rema Hanna. 2014. "Environmental Regulations, Air and Water Pollution, and Infant Mortality in India." *American Economic Review*, 104(10): 3038–72.

Greenstone, Michael, Guojun He, Ruixue Jia, and Tong Liu. 2022. "Can Technology Solve the Principal-Agent Problem? Evidence from China's War on Air Pollution." *American Economic Review: Insights*, 4(1): 54–70.

Huang, Zhangkai, Jinyu Liu, Guangrong Ma, and Lixin Colin Xu. 2024. "Political determinants of privatizations in China: A natural experiment based on politician career concerns." *Journal of Corporate Finance*, 87: 102620.

Kahn, Matthew E., Pei Li, and Daxuan Zhao. 2015. "Water Pollution Progress at Borders: The Role of Changes in China's Political Promotion Incentives." *American Economic Journal: Economic Policy*, 7(4): 223–42.

Keller, C., H. Amos, V. Buchard, A. Darmenov, S. Shen, M. Deloria Knoll, F. Villavicencio, and M. Bosilovich. 2021. "File Specification for MERRA-2 Country-Level Surface PM2.5 Monthly Mean Product." NASA Global Modeling and Assimilation Office GMAO Office Note 20 (Version 1.1).

Laffont, Jean-Jacques, and David Martimort. 1997. "Collusion Under Asymmetric Information." *Econometrica*, 65(4): 875–911.

Lipscomb, Molly, and Ahmed Mushfiq Mobarak. 2016. "Decentralization and Pollution Spillovers: Evidence from the Re-drawing of County Borders in Brazil*." *The Review of Economic Studies*, 84(1): 464–502.

Marion, Justin, and Jeremy West. 2024. "Socioeconomic Disparities in Privatized Pollution Remediation: Evidence from Toxic Chemical Spills." *American Economic Journal: Applied Economics*, 16(3): 219–49.

Mookherjee, Dilip. 2012. "Incentives in Hierarchies." In *The Handbook of Organizational Economics.* , ed. Robert Gibbons and John Roberts, 1076–1120. Princeton, NJ:Princeton University Press.

Mookherjee, Dilip, and Masatoshi Tsumagari. 2023. "Regulatory mechanism design with extortionary collusion." *Journal of Economic Theory*, 208: 105614.

Ortner, Juan, and Sylvain Chassang. 2018. "Making Corruption Harder: Asymmetric Information, Collusion, and Crime." *Journal of Political Economy*, 126(5): 2108–2133.

Pierce, Lamar, and Michael W. Toffel. 2013. "The Role of Organizational Scope and Governance in Strengthening Private Monitoring." *Organization Science*, 24(5): 1558–1584.

Prendergast, Canice. 1993. "A Theory of "Yes Men"." *The American Economic Review*, 83(4): 757–770.

Rahman, David. 2012. "But Who Will Monitor the Monitor?" *American Economic Review*, 102(6): 2767–97.

Roth, Jonathan, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe. 2023. "What's trending in difference-in-differences? A synthesis of the recent econometrics literature." *Journal of Econometrics*, 235(2): 2218–2244.

Sant'Anna, Pedro H.C., and Jun Zhao. 2020. "Doubly robust difference-in-differences estimators." *Journal of Econometrics*, 219(1): 101–122.

Shleifer, Andrei, and Robert W. Vishny. 1994. "Politicians and Firms." *The Quarterly Journal of Economics*, 109(4): 995–1025.

Short, Jodi L., Michael W. Toffel, and Andrea R. Hugill. 2016. "Monitoring global supply chains." *Strategic Management Journal*, 37(9): 1878–1897.

Strausz, Roland. 1997. "Delegation of Monitoring in a Principal-Agent Relationship." *The Review of Economic Studies*, 64(3): 337–357.

Strulovici, Bruno. 2021. "Learning and Corruption on Monitoring Chains." *AEA Papers and Proceedings*, 111: 544–48.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects." *Journal of Econometrics*, 225(2): 175–199. Themed Issue: Treatment Effect 1.

Tanaka, Shinsuke. 2015. "Environmental regulations on air pollution in China and their impact on infant mortality." *Journal of Health Economics*, 42: 90–103.

Tirole, Jean. 1986. "Hierarchies and Bureaucracies: On the Role of Collusion in Organizations." *The Journal of Law, Economics, and Organization*, 2(2): 181–214.

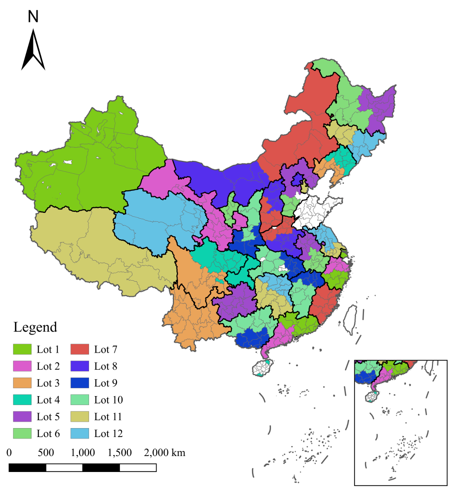
van Donkelaar, Aaron, Melanie S. Hammer, Liam Bindle, Michael Brauer, Jeffery R. Brook, Michael J. Garay, N. Christina Hsu, Olga V. Kalashnikova, Ralph A. Kahn, Colin Lee, Robert C. Levy, Alexei Lyapustin, Andrew M. Sayer, and Randall V. Martin. 2021. "Monthly Global Estimates of Fine Particulate Matter and Their Uncertainty." *Environmental Science & Technology*, 55(22): 15287–15300. PMID: 34724610.

Vannutelli, Silvia. 2022. "From Lapdogs to Watchdogs: Random Auditor Assignment and Municipal Fiscal Performance." National Bureau of Economic Research Working Paper 30644.

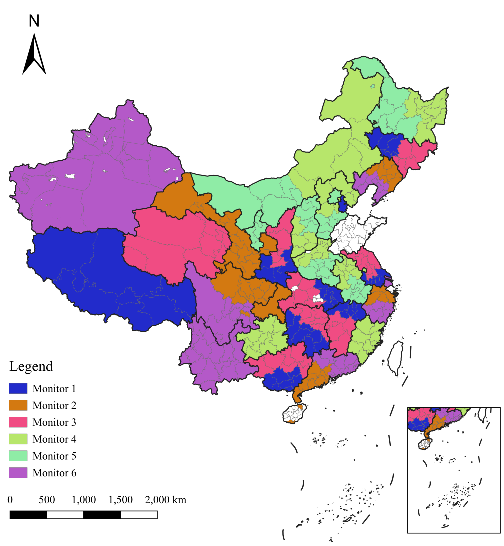
Xi, Tianyang, Yang Yao, and Muyang Zhang. 2018. "Capability and opportunism: Evidence from city officials in China." *Journal of Comparative Economics*, 46(4): 1046–1061.

Yang, Lin, Yatang Lin, Jin Wang, and Fangyuan Peng. 2024. "Achieving Air Pollution Control Targets with Technology-Aided Monitoring: Better Enforcement or Localized Efforts?" *American Economic Journal: Economic Policy*, 16(4): 280–315.

Yao, Yang, Lixing Li, Tianyang Xi, He Wang, Feng Wan, Qian Zhang, Songrui Liu, and Shundong Zhang. 2022. "CCER Officials Dataset."



(a) Bidding Lots for Outsourcing the O&M of National Air Monitoring Stations



(b) Contracts of the 6 O&M Firms

Figure 1: Geographic Distribution of Bidding Lots and Firms Assignment

Notes: This figure outlines the geographical distribution of the 12 lots up for bid (panel (a)) and the cities assigned to each of the 6 winning firm. Each "lot" refers to a bidding section covering a set of cities.

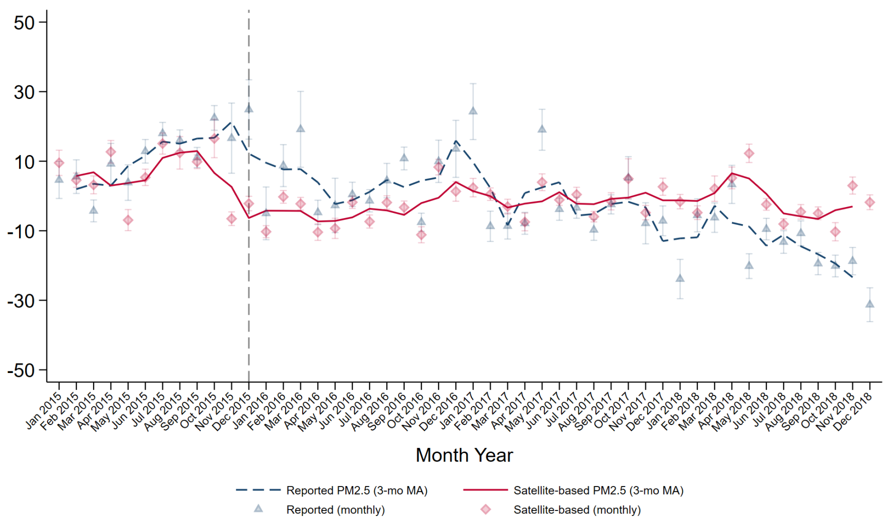


Figure 2: Reported and Satellite-based $PM_{2.5}$ Trends

Notes: This figure averages city-month maximum $PM_{2.5}$ readings. To construct the figure, we residualize the panel using city and month fixed effects to remove city-specific and seasonal patterns. The darker lines show centered three-month moving averages ($t-1,\ t,\ t+1$) to smooth month-to-month noise, with the raw monthly readings shown as points with 90% confidence intervals.

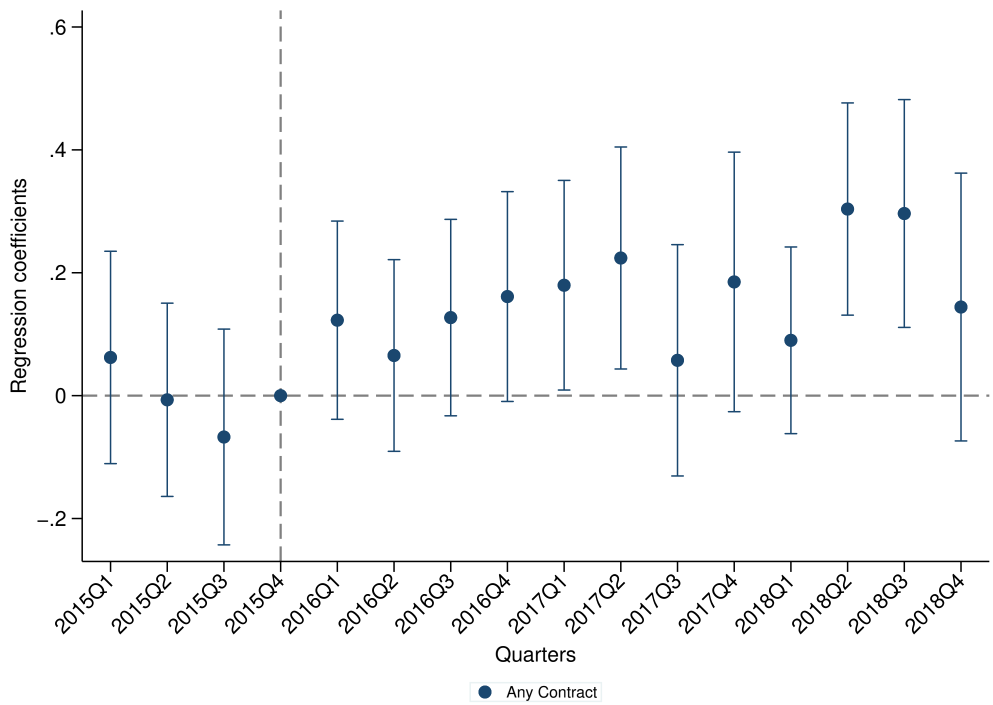
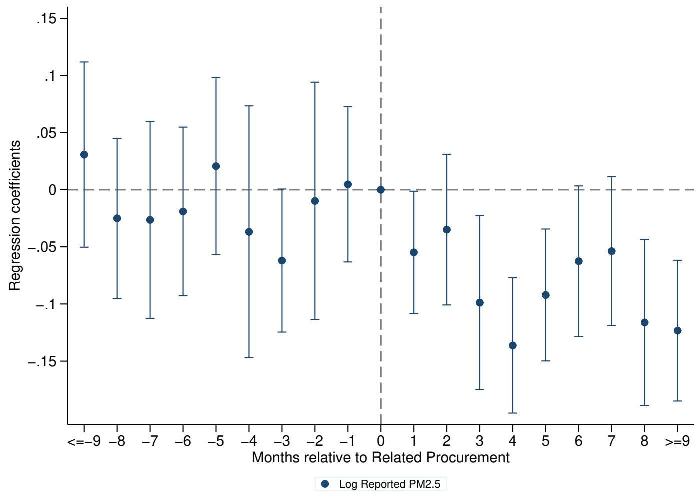
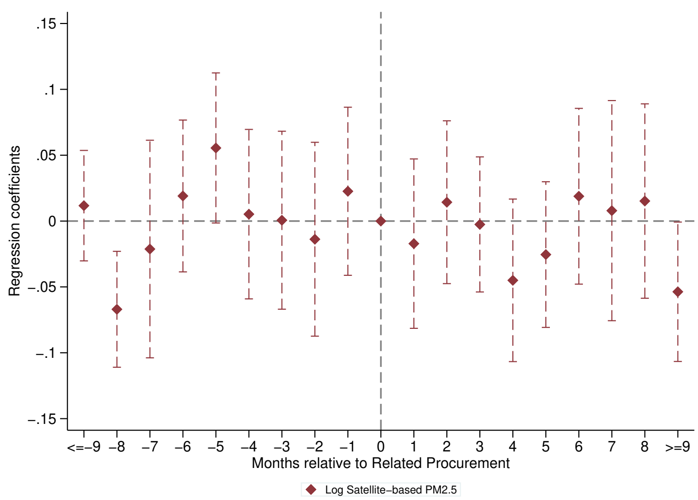


Figure 3: Dynamics of Related Procurement Around the Outsourcing Reform

Notes: We estimate the event-study specification $AnyContract_{c,f,q} = \sum_{k=2015Q1}^{2018Q4} \beta_k Treat_{c,f} \times Quarter_k + \delta_{c,f} + \theta_q + \mu_{c,y} + \nu_{f,y} + \lambda_c q + \kappa_f q + \varepsilon_{c,f,q}$, where $AnyContract_{c,f,q}$ is an indicator equal to 1 if the local government in city c and O&M firm f signed a procurement contract in quarter q, and 0 otherwise. $Related_{c,f}$ indicates whether the O&M firm f is assigned by the central government to operate the monitoring station in city c. In addition to city-firm pair fixed effects $\delta_{c,f}$ and year-quarter fixed effects θ_q, we also incorporate firm-by-year fixed effects $\nu_{f,y}$, city-by-year fixed effects $\mu_{c,y}$, city specific trends $\lambda_c q$ and firm specific trends $\kappa_f q$. See text for details. The figure displays the coefficient estimates along with their 90% confidence intervals. Standard errors are clustered at the city-firm pair level.



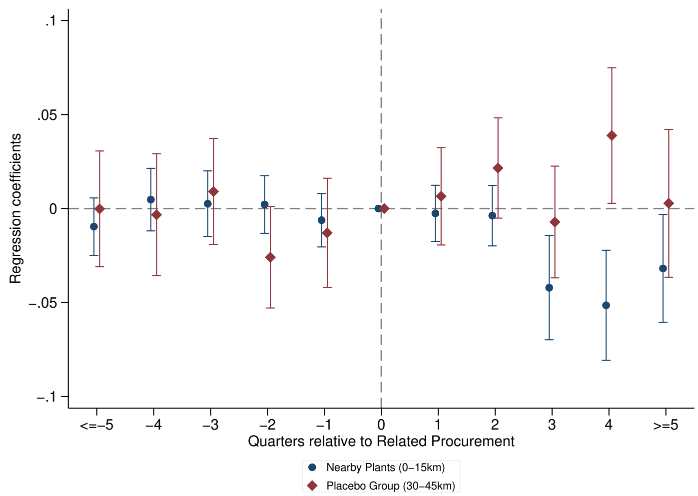
(a) Log Reported $PM_{2.5}$



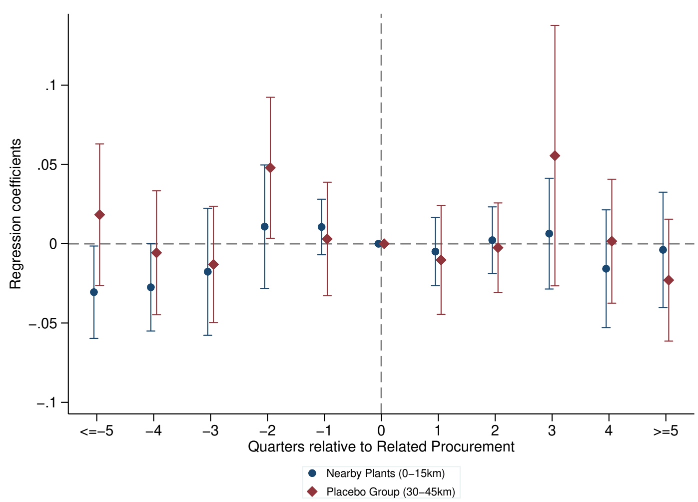
(b) Log Satellite-based $PM_{2.5}$

Figure 4: Event Study on Measured $PM_{2.5}$ Concentrations Around the Signing of Related Procurement Contracts

Notes: This figure shows the evolution of measured $PM_{2.5}$ concentration around the signing of a procurement contract between the local government and the firm assigned O&M responsibilities for the city. Please see text for details on the estimation. Panel (a) shows $PM_{2.5}$ concentration as measured by ground-level monitoring stations, while panel (b) shows $PM_{2.5}$ concentration estimates using satellite data. Note that period -9 denotes the ninth month prior to procurement and all preceding months, while period 9 denotes the ninth month after procurement and all subsequent months. The specification includes meteorological controls, province-by-year-quarter and operator-by-year-quarter fixed effects, as well as city-specific linear time trends. Standard errors are clustered at the city level. The figure plots the coefficient estimates for each period together with their 90% confidence intervals.



(a) Air-pollution-related Enforcement



(b) Other Enforcement

Figure 5: Enforcement Intensity Around the Signing of Related Procurement Contracts

Notes: This figure presents estimates from an event study specification that tracks changes in local enforcement actions surrounding the first procurement contract signed between a city and the firm with O&M responsibilities. We show the results for two subsamples. First, we show the "nearby" group of plants located within 15 kilometers of a monitoring station. Second, we show for comparison enforcement actions against plants located 30-45 kilometers from a monitoring station. The specification follows column (1) in Table 3, which incorporates province-by-year-quarter and industry-by-year-quarter fixed effects, along with year-quarter interactions for plants' 2013 size, leverage, and ROA. Panel (a) focuses on enforcement actions targeting air pollution violations. Panel (b) presents a placebo test using enforcement actions related to other types of pollution (e.g., noise, water, and soil). Both panels provide point estimates with 90% confidence intervals.

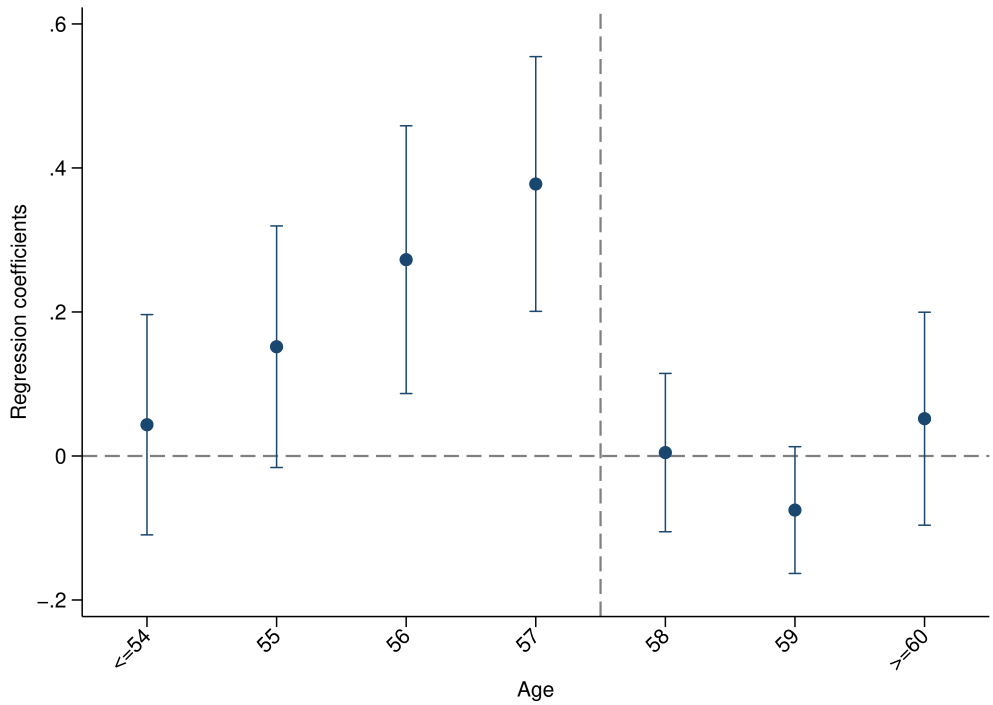


Figure 6: Heterogeneous Effects Shaped by Political Incentives

Notes: This figure displays estimates of the how outsourcing reform affected local government procurement contracting, allowing the relationship to vary with city party secretary's age at the time of the 2018 National People's Congress. The point estimates are derived from a specification based on Equation 1, but allowing the effect of reform to vary with party secretary age; see text for details. Note that the sample excludes the four centrally administered cities of Beijing, Tianjin, Chongqing, and Shanghai, and *Age* is the city Party secretary's age at the time of the 13$^{\text{th}}$ National People's Congress in 2018. The estimated specification controls for firm-city pair fixed effects and year-quarter fixed effects. Standard errors are clustered at the city-firm pair level.

Table 1: Outsourcing Reform and Related Procurement Contracts

DV	Any Contract			
	(1)	(2)	(3)	(4)
Related×Post2016	0.104***	0.104***	0.166***	0.166***
	(0.034)	(0.034)	(0.039)	(0.040)
Related	-0.049*			
	(0.029)			
Post2016	-0.018			
	(0.023)			
Firm-City Pair FE	N	Y	Y	Y
Yr-Qrt FE	N	Y	Y	Y
City-Year FE	N	N	Y	Y
Firm-Year FE	N	N	Y	Y
City Yr-Qrt Trend	N	N	N	Y
Firm Yr-Qrt Trend	N	N	N	Y
Observations	2,048	2,048	2,048	2,048
R-squared	0.006	0.185	0.336	0.389
Pre-reform DV Mean	0.125	0.125	0.125	0.125
Pre-reform DV SD	0.331	0.331	0.331	0.331

Notes: The sample in this analysis is restricted to city-firm pairs with at least one procurement transaction, and the resulting dataset is organized as a balanced panel over the period 2015Q1-2018Q4. *Any Contract* indicates whether there is a transaction between firm f and local government c in year-quarter q, and *Related* denotes that firm f has O&M responsibility for city c's air quality monitoring stations. Standard errors are clustered at the city-firm pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2: Reported and Satellite-based Pollution Data Following the Signing of (Related) Procurement Contracts

	Ground-based Data			Satellite-based Data	
DV	log$PM_{2.5}$	logPM_{10}	logAQI	log$PM_{2.5}$	Difference
	(1)	(2)	(3)	(4)	(5)
PostProcure	-0.056***	-0.042**	-0.033**	0.001	-0.056***
	(0.018)	(0.017)	(0.014)	(0.016)	(0.021)
Meteorological Controls	Y	Y	Y	Y	Y
Station FEs	Y	Y	Y	Y	Y
Day FEs	Y	Y	Y	Y	Y
Operator × YrQrt FEs	Y	Y	Y	Y	Y
Province × YrQrt FEs	Y	Y	Y	Y	Y
City Time Trends	Y	Y	Y	Y	Y
Observations	1,490,148	1,489,698	1,491,138	1,490,333	1,488,141
R-squared	0.591	0.604	0.584	0.616	0.470

Notes: The sample is a station-day panel for the period 2016-2018. Columns (1)-(3) display the results in which the dependent variables are the natural logarithms of reported air pollutants as measured by $PM_{2.5}$, PM_{10}, and AQI, respectively. Column (4) displays the results where the dependent variable is logarithm of satellite-based $PM_{2.5}$ measurements. Column (5) displays the results in which the dependent variable is difference between the logarithm of $PM_{2.5}$ as measured by ground-based monitoring stations versus satellite-based estimates. $PostProcure$ indicates the periods following the month when a local government in city c first signed a procurement contract with the O&M firm assigned to operate its air quality monitoring stations. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Related Procurement and Pollution Enforcement

DV	Enforcement				
	Air Pollution				Other Pollution
	(1)	(2)	(3)	(4)	(5)
PostProcure×I(distance≤15)	-0.022**	-0.027**			-0.001
	(0.009)	(0.011)			(0.016)
PostProcure×I(distance≤10)			-0.028***		
			(0.010)		
PostProcure×I(distance≤20)				-0.027**	
				(0.011)	
PostProcure	0.013*				
	(0.008)				
Polluter FE	Y	Y	Y	Y	Y
Province-by-Yr-Qrt FE	Y	N	N	N	N
City-by-Yr-Qrt FE	N	Y	Y	Y	Y
Ind-by-Yr-Qrt FE	Y	Y	Y	Y	Y
Size-by-Yr-Qrt FE	Y	Y	Y	Y	Y
Lev-by-Yr-Qrt FE	Y	Y	Y	Y	Y
Roa-by-Yr-Qrt FE	Y	Y	Y	Y	Y
Observations	119,664	119,664	92,304	140,760	119,664
R-squared	0.118	0.151	0.161	0.144	0.139
Pre-event DV Mean	0.029	0.029	0.029	0.029	0.071
Pre-event DV SD	0.168	0.168	0.169	0.168	0.257

Notes: PostProcure indicates the periods following the quarter when a local government in city c first signed a procurement contract with the O&M firm assigned to operate its air quality monitoring stations. *distance* is the geographical distance between the polluter and its nearest air quality monitoring station. For each regression, the reference group is polluters located 30–45 km from the monitoring station. For columns (1)-(5), the dependent variable is an indicator variable denoting whether there is any local regulatory punishment against the polluter for its air pollution, while for column (6), it indicates the presence of regulatory enforcement targeting other types of pollution. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Rainfall, Related Procurement, and Reported Pollution

	Ground-based Data		
DV	log$PM_{2.5}$	logPM_{10}	logAQI
	(1)	(2)	(3)
PostProcure × Rainfall	0.021***	0.012**	0.013**
	(0.008)	(0.005)	(0.005)
PostProcure	-0.056***	-0.042**	-0.033**
	(0.018)	(0.017)	(0.014)
Rainfall	-0.018***	-0.031***	-0.042***
	(0.002)	(0.002)	(0.002)
Meteorological Controls	Y	Y	Y
Station FEs	Y	Y	Y
Day FEs	Y	Y	Y
Operator × YrQrt FEs	Y	Y	Y
Province × YrQrt FEs	Y	Y	Y
City Time Trends	Y	Y	Y
Observations	1,487,377	1,486,927	1,488,371
R-squared	0.591	0.606	0.588

Notes: Rainfall is standardized by subtracting the city-year mean and dividing by the corresponding standard deviation. *PostProcure* indicates the periods following the month when a local government in city c first signed a procurement contract with the O&M firm assigned to operate its air quality monitoring stations. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

APPENDIX FOR ONLINE PUBLICATION ONLY

Appendix A Supplementary Details on Data

1. Pollutant Measures

The national monitoring stations provide hourly instantaneous measurements of $PM_{2.5}$, PM_{10}, and the Air Quality Index (AQI), as well as hourly updated 24-hour moving averages of $PM_{2.5}$ and PM_{10}. In our analysis, we use the daily averages of these indicators, specifically the daily average of the hourly AQI and the daily averages of the hourly 24-hour moving averages of $PM_{2.5}$ and PM_{10}. We focus on the 24-hour moving averages because environmental air quality standards and policy evaluations are typically based on daily or 24-hour concentration limits.

As a robustness check, we complement our main analysis with satellite-derived $PM_{2.5}$ from the Atmospheric Composition Analysis Group (dataset `V5.GL.05.02`), which is available at a $0.1° \times 0.1°$ spatial resolution but only at a monthly frequency. This dataset provides annual and monthly estimates of ground-level fine particulate matter ($PM_{2.5}$) for 1998-2023 by combining Aerosol Optical Depth (AOD) retrievals (Dark Target, Deep Blue, and MAIAC) from multiple NASA satellite instruments with the GEOS-Chem chemical transport model, and subsequently calibrating the results against global ground-based observations using a Geographically Weighted Regression (GWR). See van Donkelaar et al. (2021) for further details.

2. Environmental Regulatory Enforcement

We obtain environmental enforcement records issued by local Environmental Protection Bureaus (EPBs) from PKULaw. The dataset contains 252,938 case-level observations for 2015-2018, and our analysis focuses on the subsample from 2016-2018. The PKULaw database collects administrative penalty decisions disclosed by local EPBs. Appendix Figure A5 provides an illustrative example. Appendix Figure A6 depicts the monthly count of environmental enforcement actions undertaken by local EPBs between 2015 and 2018.

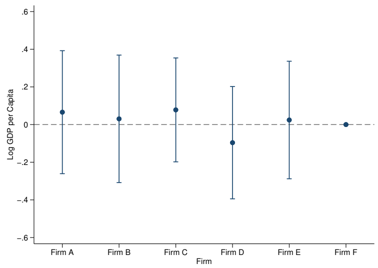
From each case, we can extract information such as the penalizing authority, the penalized party, the cause, the outcome, and the date of the penalty. Based on these documents, we can determine whether the penalty is related to air pollution. Specifically, we classify an enforcement action as air-pollution-related if the case text includes any of the following keywords: "air", "exhaust gas", "dust", "particulate matter", "sulfur dioxide", "nitrogen oxides", "gases", "ozone", "carbon monoxide", "particles", "smoke", "flue gas", "incineration", "dense smoke", or "chimney". All other cases are categorized as enforcement actions targeting other forms of pollution.

We match the names of penalized entities in the enforcement records with those in the 2013 Annual Survey of Industrial Firms (ASIF) Database, resulting in 17,982 matched industrial firms.

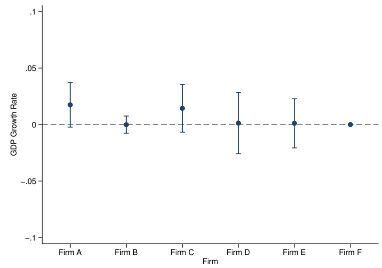
Appendix B Additional Figures and Tables

Appendix Figure A1: Water Spraying on Monitoring Station

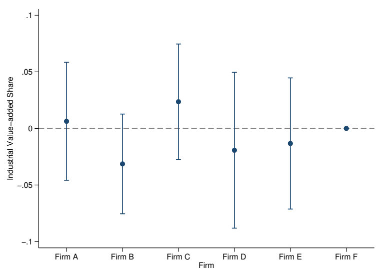
Notes: This image shows a mobile water mist cannon in operation, spraying a fine mist into the air above the air quality monitoring station. Source: The Paper, https://www.thepaper.cn/newsDetail_forward_1912250, last accessed September 30, 2025.



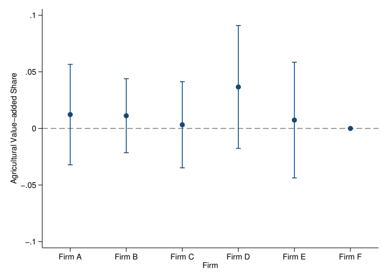
(a) Log(GRP per capita)



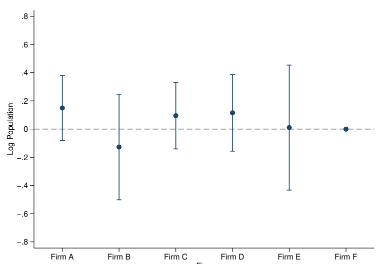
(b) GRP Growth Rate



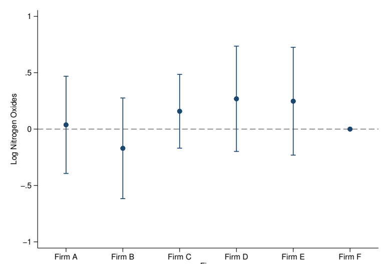
(c) Industrial Share of Value Added



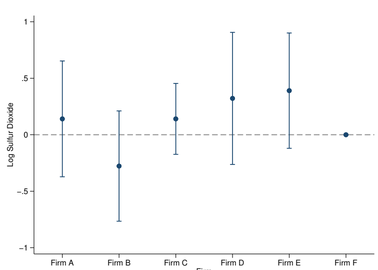
(d) Agricultural Share of Value Added



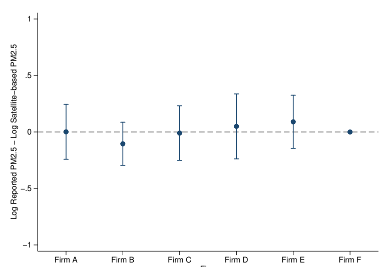
(e) Log(Population)



(f) Log(NO_x)



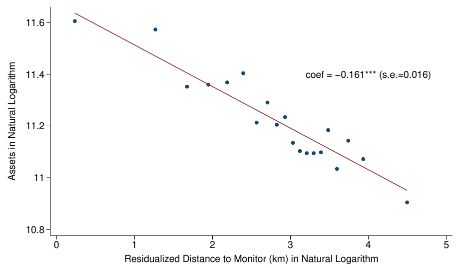
(g) Log(SO_2)



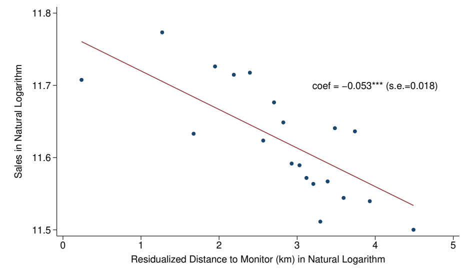
(h) $\log \mathrm{PM}_{2.5}^{\mathrm{reported}}$ - $\log \mathrm{PM}_{2.5}^{\mathrm{satellite}}$

Appendix Figure A2: Balance Tests of City-level Characteristics across O&M Firms

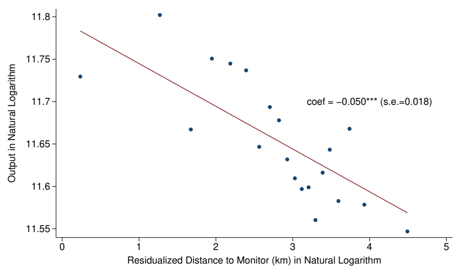
Notes: Using 2015 data, we estimate $Y_c = \alpha + \sum_{f=1}^{6} \beta_f \, Firm_f + \varepsilon_c$, where f denotes the O&M firm and c denotes the city. Characteristics include GRP per capita, GRP growth, industrial share of value added, agricultural share of value added, population, industrial SO_2 and NO_x emissions, and the average difference between $\log \mathrm{PM}_{2.5}^{\mathrm{reported}}$ and $\log \mathrm{PM}_{2.5}^{\mathrm{satellite}}$ in the first three quarters of 2015. Standard errors are clustered at the province level. We plot β_f with 90% confidence intervals.



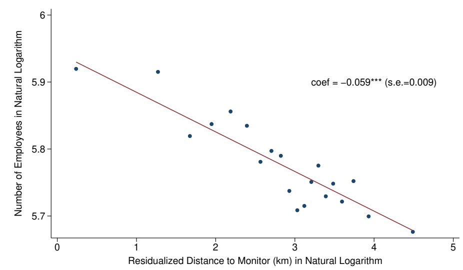
(a) Log(Assets)



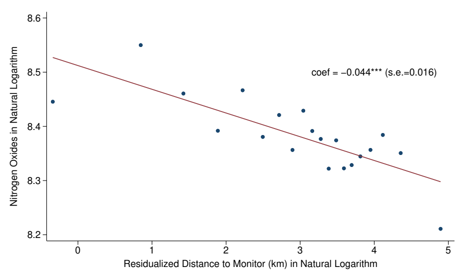
(b) Log(Sales)



(c) Log(Output)



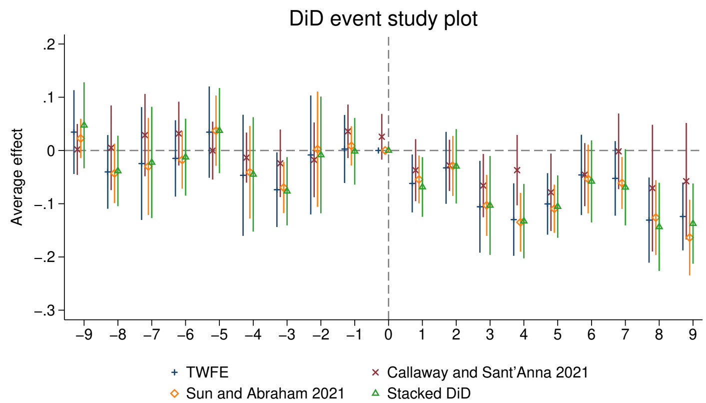
(d) Log(Number of Employees)



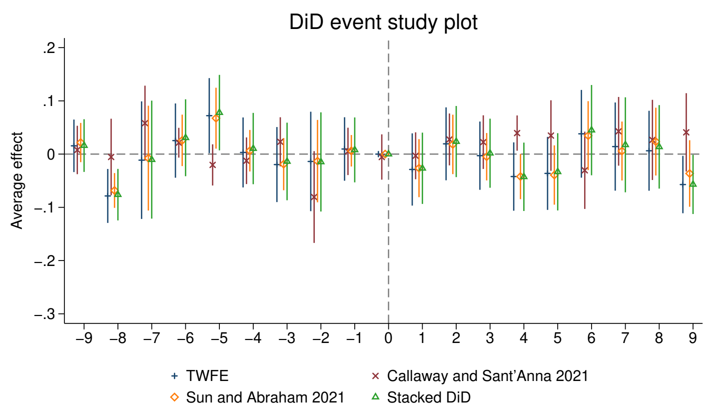
(e) Log(NO_x)

Appendix Figure A3: Non-Random Placement of National Monitoring Stations

Notes: This figure displays the correlation between firm characteristics prior to the reform and its distance from a monitoring station. Scatterplot controls for city fixed effects. Panels (a)-(d) use plants with documented environmental enforcement actions from the 2013 Annual Survey of Industrial Firms, while Panel (e) is based on plants with reported nitrogen oxide emissions in the 2014 Environmental Survey and Reporting Database. Standard errors are clustered at the city level.



(a) Log(Reported $PM_{2.5}$)



(b) Log(Satellited-based $PM_{2.5}$)

Appendix Figure A4: Alternative Event Study Models

Notes: This figure shows different staggered DiD estimators, along with their 90% confidence intervals. Standard errors are clustered at the city level. The TWFE estimates are shown as blue plus signs, estimates based on Sun and Abraham (2021) are shown as orange diamonds, estimates based on Callaway and Sant'Anna (2021) appear as red crosses, and the stacked DiD estimates from Cengiz et al. (2019) are marked with green triangles. Apart from the Callaway and Sant'Anna (2021) estimators, all specifications follow the same fixed effects as in Figure 4. For the Callaway and Sant'Anna (2021) estimators, we restrict the control group to never-treated units and employ the improved doubly robust estimator based on inverse probability tilting and weighted least squares (Sant'Anna and Zhao, 2020). In addition, we include province dummies as covariates.

<table>
<tr><td>Administrative Penalty Decision No.</td><td>行政处罚决定文书号：</td><td colspan="5">[redacted]〔2018〕1 号</td></tr>
<tr><td>Name of Administrative Penalty</td><td>处罚名称：</td><td colspan="5">[redacted]公司行政处罚案</td></tr>
<tr><td>Type of Administrative Penalty</td><td>处罚类别：</td><td colspan="5">罚款</td></tr>
<tr><td>Grounds for Administrative Penalty</td><td>处罚事由：</td><td colspan="5">经我局执法监察支队 2017 年 6 月 23 日调查显示，2017 年 6 月 14 日，当事人在正常生产情况下，经中国广州分析测试中心监测，污水排放口废水中的总磷浓度为 2.84 毫克/升，超过了《电镀水污染物排放标准》(DB44/1597-2015)表 1 排放限值（总磷浓度≤2 毫克/升）。</td></tr>
<tr><td>Legal Basis for Administrative Penalty</td><td>处罚依据：</td><td colspan="5">依据《中华人民共和国环境保护法》第六十条、《环境保护主管部门实施限制生产、停产整治办法》（环境保护部令第 30 号）、《中华人民共和国水污染防治法》第七十四条及《广州市环境保护局规范行政处罚自由裁量权规定》附件《环境违法行为行政处罚自由裁量适用标准》第 13（1）（C）（b）项的规定</td></tr>
<tr><td>Outcome of Administrative Penalty</td><td>处罚结果：</td><td colspan="5">责令当事人限制生产，限制生产期限为一个月，限制生产的改正方式以能达到达标排放目的为准，并处罚款 6097 元。</td></tr>
<tr><td>Name of Party Subject to the Penalty</td><td>行政相对人名称：</td><td colspan="5">[redacted]有限公司</td></tr>
<tr><td rowspan="2">ID of Party Subject to the Penalty</td><td rowspan="2">行政相对人代码：</td><td>统一社会信用代码</td><td>组织机构代码</td><td>工商登记码</td><td>税务登记号</td><td>居民身份证号码</td></tr>
<tr><td>[redacted]</td><td></td><td></td><td></td><td></td></tr>
<tr><td></td><td>法人代表姓名：</td><td colspan="5">[redacted]</td></tr>
<tr><td>Date of Penalty</td><td>处罚决定日期：</td><td colspan="5">2018/1/3</td></tr>
<tr><td>Authority Imposing the Administrative Penalty</td><td>处罚机关：</td><td colspan="5">广州市环境保护局</td></tr>
<tr><td></td><td>地方编码：</td><td colspan="5">400100</td></tr>
<tr><td></td><td>当前状态：</td><td colspan="5">正常</td></tr>
<tr><td></td><td>数据更新时间戳：</td><td colspan="5">2018/1/3</td></tr>
<tr><td></td><td>备注：</td><td colspan="5"></td></tr>
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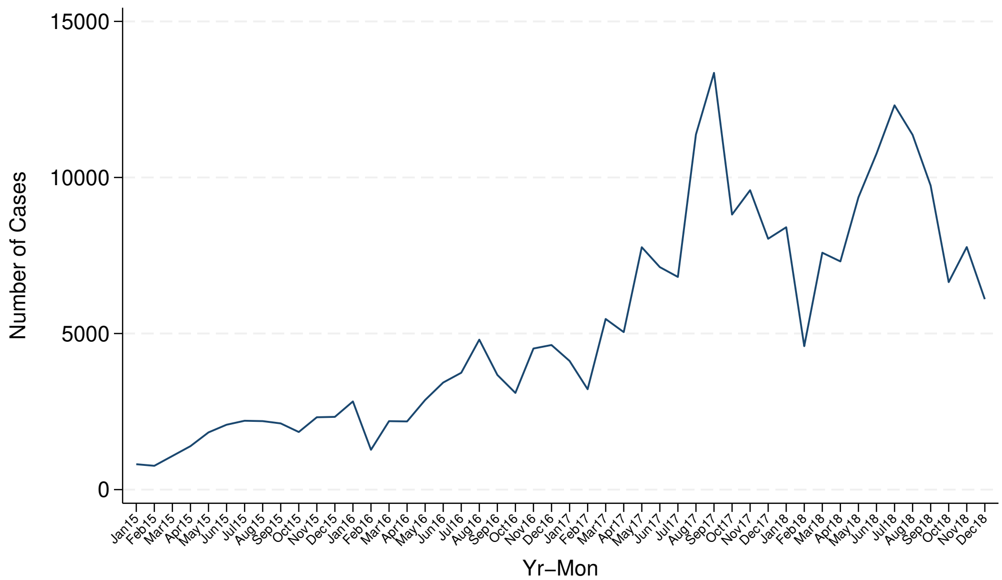
Appendix Figure A5: Administrative Penalty Document: An Illustrative Example



Appendix Figure A6: Trend of Environmental Enforcement by Local Authorities

Notes: Using case-level raw data from PKULaw, we calculate and plot the monthly number of environmental enforcement actions for the period 2015–2018.

Appendix Table A1: Outsourcing Reform and Related Procurement Contracts: Pair-Month Level Analysis

DV	Any Contract			
	(1)	(2)	(3)	(4)
Related×Post2016	0.042***	0.042***	0.055***	0.055***
	(0.014)	(0.014)	(0.016)	(0.016)
Related	-0.021*			
	(0.012)			
Post2016	-0.005			
	(0.009)			
Firm-City Pair FE	N	Y	Y	Y
Yr-Qrt FE	N	Y	Y	Y
City-Year FE	N	N	Y	Y
Firm-Year FE	N	N	Y	Y
City Yr-Qrt Trend	N	N	N	Y
Firm Yr-Qrt Trend	N	N	N	Y
Observations	6,096	6,096	6,096	6,096
R-squared	0.002	0.108	0.175	0.199
Pre-reform DV Mean	0.049	0.049	0.049	0.049
Pre-reform DV SD	0.215	0.215	0.215	0.215

Notes: Sample is restricted to city-firm pairs with at least one transaction, and the resulting dataset is collapsed as a balanced pair-month panel over the January 2015 - December 2018. *Any Contract* indicates whether there is any contract signed between the firm and the local government in the year-quarter. *Related* indicates whether the O&M firm is assigned by central government to operate the monitoring station in the city. Standard errors are clustered at the city-firm pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A2: Outsourcing Reform and Related Procurement Contracts: Including Never-Contracting Pairs

DV	Any Contract			
	(1)	(2)	(3)	(4)
Related×Post2016	0.012***	0.012***	0.012***	0.012***
	(0.004)	(0.004)	(0.003)	(0.003)
Related	0.004			
	(0.004)			
Post2016	-0.001			
	(0.001)			
Firm-City Pair FE	N	Y	Y	Y
Yr-Qrt FE	N	Y	Y	Y
City-Year FE	N	N	Y	Y
Firm-Year FE	N	N	Y	Y
City Yr-Qrt Trend	N	N	N	Y
Firm Yr-Qrt Trend	N	N	N	Y
Observations	30,816	30,816	30,816	30,816
R-squared	0.003	0.257	0.290	0.305
Pre-reform DV Mean	0.009	0.009	0.009	0.009
Pre-reform DV SD	0.095	0.095	0.095	0.095

Notes: Sample includes all city–firm pairs, even if they never transact during the sample period, and the resulting dataset is organized as a balanced panel over the 2015Q1-2018Q4. *Any Contract* indicates whether there is any contract signed between the firm and the local government in the year-quarter. *Related* indicates whether the O&M firm is assigned by central government to operate the monitoring station in the city. Standard errors are clustered at the city-firm pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A3: Correlation between Ground-Level Reported Pollutants and Satellite-based $PM_{2.5}$

DV	Log(Reported $PM_{2.5}$)	Log(PM_{10})	Log(Reported AQI)
	(1)	(2)	(3)
Log(Satellite-based PM2.5)	0.307***	0.225***	0.257***
	(0.011)	(0.008)	(0.009)
Station FE	Y	Y	Y
Day FE	Y	Y	Y
Observations	1,488,141	1,487,692	1,489,129
R-squared	0.588	0.587	0.574

Notes: Analysis is at the station-by-day level. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A4: Reported versus Satellite-based Pollution Measures after Signing of Related Procurement Contracts: Station-Month Data Structure

	Ground-based Data			Satellite-based Data	
DV	PM2.5	PM10	AQI	PM2.5	PM2.5 (ACAG)
	(1)	(2)	(3)	(4)	(5)
PostProcure	-0.056***	-0.040**	-0.035**	-0.007	-0.009
	(0.017)	(0.017)	(0.014)	(0.013)	(0.011)
Meteorological Controls	Y	Y	Y	Y	Y
Station FEs	Y	Y	Y	Y	Y
Yr-Mon FEs	Y	Y	Y	Y	Y
Operator × YrQrt FEs	Y	Y	Y	Y	Y
Province × YrQrt FEs	Y	Y	Y	Y	Y
City Time Trends	Y	Y	Y	Y	Y
Observations	49,482	49,493	49,503	49,489	49,490
R-squared	0.862	0.872	0.871	0.906	0.921

Notes: Sample is station-month panel in 2016-2018. Columns (1)-(3) display the results in which the dependent variables are the logarithm of reported air pollutant levels: $PM_{2.5}$, PM_{10}, and AQI, respectively. Column (4) displays the results where the dependent variable is Merra2 satellite-based $PM_{2.5}$. Column (5) displays the results where the dependent variable is ACAG satellite-based $PM_{2.5}$. *PostProcure* indicates the periods following the month when local governments signed a procurement contract with the O&M firm assigned to operate the air quality monitoring stations in the city. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A5: Summary Statistics

Variables	Obs	Mean	SD	P10	Median	P90
a: Prefecture-Firm-Quarter Transaction Panel						
Any Contract	2,048	0.136	0.343	0	0	1
Contract Number	2,048	0.177	0.477	0	0	1
Contract Value (1,000CNY)	2,048	696	2,590	0	0	977
distance (km)	2,048	771.598	564.134	173.561	615.6	1,636.431
b: Station-day Pollutant Panel						
Reported $PM_{2.5}$	1,490,148	44.116	36.797	14.000	34.429	83.917
Reported PM_{10}	1,489,698	78.246	66.103	28.125	62.792	142
Reported AQI	1,491,138	70.897	45.757	30.750	59.750	121
Satellite-based $PM_{2.5}$	1,490,333	31.047	19.068	10.247	28.033	54.751
c: Polluter-Quarter Enforcement Panel						
Enforcement	215,784	0.031	0.174	0	0	0
$\text{Enforcement}_{other}$	215,784	0.072	0.258	0	0	0
I(distance$\leq$15)	215,784	0.425	0.494	0	0	1
I(15$<$distance$\leq$30)	215,784	0.244	0.43	0	0	1
I(30$<$distance$\leq$45)	215,784	0.132	0.338	0	0	1

Notes: This table reports summary statistics across the different datasets used in the analysis. Panel (a) is based on the prefecture-firm-quarter transaction panel, where *distance* measures the distance between the prefecture and the headquarters of the O&M firm. Panel (b) draws on the station-day pollutant panel. Reported $PM_{2.5}$, PM_{10}, and AQI are levels published by the national monitoring stations, while satellite-based $PM_{2.5}$ is constructed from MERRA-2 reanalysis data. For both reported and satellite-based measures, the units of $PM_{2.5}$ and PM_{10} are micrograms per cubic meter ($\mu g/m^3$). Panel (c) uses the polluter-quarter enforcement panel. *Enforcement* is an indicator equal to one if the industrial firm received at least one enforcement action related to air pollution from the local Environmental Protection Bureau during the quarter, while $Enforcement_{other}$ refers to enforcement actions related to other types of pollution (e.g., water or noise). Here, *distance* measures the distance between the polluter and the nearest national monitoring station. We provide the fraction of polluters that are less than 15 kilometers from the nearest monitoring station and those that are between 30 and 45 kilometers, as those are the groups we use in our analysis.

Appendix Table A6: Comparing Industrial Firms Near versus Further Away from National Monitoring Stations

Distance to Monitor	30-45km (1)	0-15km (2)	Dif (3)
	Panel a: ASIF 2013		
asset (in million CNY)	244.297	482.153	237.856***
	(1264.322)	(3663.557)	(76.681)
output (in million CNY)	306.106	513.905	207.798***
	(1422.348)	(3383.491)	(71.677)
sales (in million CNY)	295.256	511.099	215.843***
	(1399.346)	(3478.235)	(73.373)
number of employees	414.133	586.045	171.912***
	(431.578)	(2979.485)	(61.533)
Observations	2,368	7,638	
	Panel b: ESR 2014		
NO_x (in Tons)	103.736	160.044	56.307***
	(822.968)	(1173.785)	(11.255)
Observations	13,120	35,375	

Notes: This table displays the coefficient estimates of the correlation between the distance to the monitoring station and plants' size. Columns (1) and (2) present group means, with standard deviations in parentheses. Column (3) presents the difference in means, with standard errors from t-tests in parentheses. Panel (a) uses plants with documented environmental enforcement actions from the 2013 Annual Survey of Industrial Firms, while panel (b) is based on plants with reported nitrogen oxide emissions in the 2014 Environmental Survey and Reporting (ESR) Database, which is compiled by the Ministry of Environmental Protection and covers major poluters responsible for approximately 65% of local emissions.

Appendix Table A7: Comparing Cities With and Without Related Procurement Contracts

Variable	Cities without Related Procurement (1)	Cities with Related Procurement (2)	Diff (3)
a: Station-day Pollutant Panel			
Reported $PM_{2.5}$	42.601	54.052	11.451***
	(35.122)	(45.067)	(0.088)
Reported PM_{10}	75.732	94.710	18.978***
	(65.425)	(68.127)	(0.159)
Reported AQI	68.914	83.871	14.958***
	(44.041)	(53.928)	(0.110)
Satellite-based $PM_{2.5}$	30.227	36.429	6.202***
	(18.844)	(19.647)	(0.046)
Observations	1,294,567	197,778	
b: Polluter-Quarter Enforcement Panel			
Enforcement	0.029	0.039	0.010***
	(0.168)	(0.194)	(0.001)
Enforcement_other	0.074	0.066	-0.008***
	(0.261)	(0.247)	(0.001)
I(distance≤15)	0.435	0.388	-0.046***
	(0.496)	(0.487)	(0.003)
I(15<distance≤30)	0.238	0.267	0.029***
	(0.426)	(0.442)	(0.002)
I(30<distance≤45)	0.120	0.175	0.055***
	(0.325)	(0.380)	(0.002)
Observations	169,356	46,428	
c: City-level Cross-sec (2015)			
log(GRPpc)	10.697	10.693	-0.004
	(0.525)	(0.545)	(0.096)
GRPgrowth	0.076	0.077	0.002
	(0.032)	(0.020)	(0.006)
AgriShare	0.125	0.119	-0.006
	(0.083)	(0.064)	(0.015)
IndShare	0.465	0.465	0.000
	(0.097)	(0.103)	(0.018)
log(Pop)	5.814	6.314	0.500***
	(0.700)	(0.576)	(0.125)
log(NO_x)	10.426	10.777	0.351**
	(0.930)	(0.731)	(0.166)
log(SO_2)	11.518	11.895	0.378*
	(1.223)	(1.018)	(0.223)
Observations	257	34	

Notes: Columns (1) and (2) present group means, with standard deviations in parentheses. Column (3) presents the difference in means, with standard errors from t-tests in parentheses. Panel (a) draws on the station-day pollutant panel from 2016 to 2018. Reported $PM_{2.5}$, PM_{10}, and AQI are levels published by the national monitoring stations, while satellite-based $PM_{2.5}$ is constructed from MERRA-2 reanalysis data. For both reported and satellite-based measures, the units of $PM_{2.5}$ and PM_{10} are micrograms per cubic meter ($\mu g/m^3$). Panel (b) uses the polluter-quarter enforcement panel from 2016 to 2018. *Enforcement* is an indicator equal to one if the industrial firm received at least one enforcement action related to air pollution from the local EPB during the quarter, while *Enforcement_other* refers to enforcement actions related to other types of pollution (e.g., water or noise). Here, *distance* measures the distance between the polluter and the nearest national monitoring station. Panel (c) is based on cross-sectional data on city-level characteristics for 2015. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A8: Outsourcing Reform and Related Procurement Contracts: Alternative Dependent Variables and Specifications

DV	Contract Number					Contract Value
	Linear Model				Poisson Model	
	(1)	(2)	(3)	(4)	(5)	(6)
Related×Post2016	0.139***	0.139***	0.211***	0.211***	0.795***	0.884*
	(0.047)	(0.047)	(0.061)	(0.063)	(0.303)	(0.512)
Related	-0.056					
	(0.044)					
Post2016	-0.030					
	(0.031)					
Firm-City Pair FE	N	Y	Y	Y	Y	Y
Yr-Qrt FE	N	Y	Y	Y	Y	Y
City-Year FE	N	N	Y	Y	N	N
Firm-Year FE	N	N	Y	Y	N	N
City Yr-Qrt Trend	N	N	N	Y	N	N
Firm Yr-Qrt Trend	N	N	N	Y	N	N
Observations	2,048	2,048	2,048	2,048	2,048	2,032
R-squared	0.006	0.217	0.366	0.424	0.199	0.421
Pre-reform DV Mean	0.166	0.166	0.166	0.166		
Pre-reform DV SD	0.470	0.470	0.470	0.470		

Notes: Sample is restricted to city-firm pairs with at least one transaction, and the resulting dataset is organized as a balanced panel over the 2015Q1-2018Q4. *Contract Number* and *Contract Value* is the number and value of contracts between the firm and the local government in the year-quarter, respectively. *Related* indicates whether the O&M firm is assigned by central government to operate the monitoring station in the city. Standard errors are clustered at the city-firm pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A9: Reported versus Satellite-based Pollution Measures after Related Procurement: Alternative Specifications

DV	$\log PM_{2.5}$				
	(1)	(2)	(3)	(4)	(5)
	Panel a: Ground-based Data				
PostProcure	-0.030**	-0.026*	-0.052***	-0.061***	-0.056***
	(0.015)	(0.015)	(0.014)	(0.014)	(0.018)
	Panel b: Satellite-based Data				
PostProcure	0.012	0.009	-0.000	-0.006	0.001
	(0.019)	(0.021)	(0.009)	(0.009)	(0.016)
Meteorological Controls	Y	Y	Y	Y	Y
City FEs	Y	N	N	N	N
YrMon FEs	Y	N	N	N	N
Station FEs	N	Y	Y	Y	Y
Day FEs	N	Y	Y	Y	Y
Province × YrQrt FEs	N	N	Y	Y	Y
Operator × YrQrt FEs	N	N	N	Y	Y
City Time Trends	N	N	N	N	Y

Notes: Sample is station-month panel in 2016-2018. Panel (a) displays the results in which the dependent variables are reported air pollutants level: $PM_{2.5}$. Panel (b) displays the results where the dependent variable is satellite-based $PM_{2.5}$ within 10km of the station. *PostProcure* indicates the periods following the month when local governments signed procurement contracts with the O&M firm assigned to operate the air quality monitoring stations in this city. Standard errors are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A10: Political Incentives and Allocation of Government Contracts

DV	Any Contract					
Sample		All		Omitting centrally administered cities		
	(1)	(2)	(3)	(4)	(5)	(6)
Related×Post2016×I(Age≤57)	0.106	0.138**	0.138**	0.131*	0.218***	0.218***
	(0.073)	(0.067)	(0.069)	(0.075)	(0.063)	(0.065)
Related×Post2016	0.052	0.110**	0.110**	0.025	0.035	0.035
	(0.043)	(0.048)	(0.050)	(0.046)	(0.045)	(0.046)
Post2016×I(Age≤57)	-0.092**			-0.100**		
	(0.046)			(0.045)		
Related×I(Age≤57)	-0.125	-0.153**	-0.153**	-0.132*	-0.213***	-0.213***
	(0.076)	(0.062)	(0.064)	(0.077)	(0.061)	(0.062)
I(Age≤57)	0.115**			0.115**		
	(0.048)			(0.048)		
Firm-City Pair FE	Y	Y	Y	Y	Y	Y
Yr-Qrt FE	Y	Y	Y	Y	Y	Y
City-Year FE	N	Y	Y	N	Y	Y
Firm-Year FE	N	Y	Y	N	Y	Y
City Yr-Qrt Trend	N	N	Y	N	N	Y
Firm Yr-Qrt Trend	N	N	Y	N	N	Y
Observations	2,044	2,044	2,044	1,980	1,980	1,980
R-squared	0.188	0.337	0.390	0.190	0.343	0.395
Pre-reform DV Mean	0.125	0.125	0.125	0.125	0.125	0.125
Pre-reform DV SD	0.331	0.331	0.331	0.331	0.331	0.331

Notes: Sample is restricted to city-firm pairs with at least one transaction. *Any Contract* indicates whether there is any contract signed between the firm and the local government in the year-quarter. *Age* denotes the age of the city Party secretary at the time of the 2018 NPC. *Related* indicates whether the O&M firm is assigned by central government to operate the monitoring station in the city. Standard errors are clustered at the firm-city pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix Table A11: Distance and Allocation of Government Contracts

DV	Any Contract		
	(1)	(2)	(3)
Related×Post2016×LogDistance	0.001	0.035	0.035
	(0.029)	(0.042)	(0.043)
Related×Post2016	0.090	-0.061	-0.061
	(0.181)	(0.274)	(0.282)
Post2016×LogDistance	-0.060***	-0.017	-0.017
	(0.014)	(0.019)	(0.020)
Firm-City Pair FE	Y	Y	Y
Yr-Qrt FE	Y	Y	Y
City-Year FE	N	Y	Y
Firm-Year FE	N	Y	Y
City Yr-Qrt Trend	N	N	Y
Firm Yr-Qrt Trend	N	N	Y
Observations	2,048	2,048	2,048
R-squared	0.191	0.336	0.389
Pre-reform DV Mean	0.125	0.125	0.125
Pre-reform DV SD	0.331	0.331	0.331

Notes: Sample is restricted to city-firm pairs with at least one transaction. *Any Contract* indicates whether there is any contract signed between the firm and the local government in the year-quarter. *LogDistance* is the geographical distance (in kilometers) between the firm and the local government. *Related* indicates whether the O&M firm was assigned by the central government to operate the monitoring station in the city. Standard errors are clustered at the firm-city pair level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.