Online Appendix for "Achieving Air Pollution Control Targets with Technology-aided Monitoring: Better Enforcement or Localized Efforts?"

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A1. Institutional Details and Evidence on Strategic Cleaning

ENVIRONMENTAL REGULATIONS IN CHINA. — In this section, we review three particular regulatory policies that change the evaluation rules for local officials and thus directly affect their incentives for pollution control. The major policy document that set the stage for China's "war on pollution" is the "Action Plan for Air Pollution Prevention and Control" (Air Ten hereafter), announced in September 2013. To better implement the Air Ten at the local level, the Ministry of Ecology and Environment (MEE), Chinese equivalence of EPA, signed a "Target Responsibility Agreement (*mubiao zerenshu*) for Atmospheric Pollution Prevention and Control" (Target hereafter)—essentially performance contracts–with 31 provinces after Air Ten was issued. Another key document, titled "Notice of the General Office of the State Council on Performance Assessment Measures for Air Pollution Prevention and Control Action Plan" (Document NO. GUOBANFA[2014]21, Assessment hereafter), issued on April 30th, 2014, provides more details on environmental performance assessment metrics with respect to the Air Ten action plan. Table A1 of the Appendix contains further detail on the three documents.

The key points of these documents are summarized below:

1) **Air Ten**—Air Ten set the national guidelines on air quality improvement targets and laid out ten tasks. These tasks include industrial upgrading, clean production, management of coal and oil sources, regulation of coal-power plants, vehicle pollution control, and so on.

2) **Target**—Each provincial government signed its Target Responsibility Agreement with the MEE. In the agreements, provincial leaders pledge to attain certain air pollution reduction targets for the 2013-2017 period using the 2012 pollution level as the base. There are two major components to the target: air quality targets and the progress with the ten tasks. Notably, the air quality targets vary across provinces: for some, the focus was on reducing $PM_{2.5}$ concentration levels, while for others, the goal was set to reduce PM_{10}. To ensure accountability and implementation, the provincial targets are further decomposed and allocated to city governments, again through the target responsibility system.

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3) **Assessment**—The Assessment lays out metrics of both the air quality targets and tasks progress. The final score will be a minimum of two (both standardized to have a full mark of 100).

    a) Air quality improvement is measured as the annual average concentration reduction rate of $PM_{2.5}$ (PM_{10}).The annual concentration of $PM_{2.5}$ (PM_{10}) of a city is measured as the annual arithmetic mean concentrations across its central monitors.

    b) Key tasks on the prevention and control of air pollution: a scoring system with deduction points from violations to performance standards of the ten tasks, which could also vary by provinces (An example of the deduction point is: "gas stations in a region will be randomly checked for qualified fuel supply. Non-compliant fuel sales will result in a penalty of 1 point.").

4) **Assessment**—Regions that fail to pass the annual assessment will face the following penalties:

    a) Local leaders would be summoned for questioning by upper-level officials from the province or other departments.

    b) Financial penalties will be imposed, such as a reduction in the central grants to the local governments.

    c) The procedures for approving new projects that have environmental impacts will be suspended.

5) **Assessment**—Falsification of monitoring data during the assessment results in a disqualification result, followed by a serious investigation by the Supervision Organs.

LOCAL GOVERNMENT DOCUMENTS AND NEWS ARTICLES RELATED TO STRATEGIC CLEANING. — In this section, we perform additional analysis on 121 local government documents that mandate strategic cleaning in their pollution control action plans. In the upper panel of Figure A1, we create a heat map to visualize the spatial distribution of those official documents. In the lower panel, we plot the histogram of the related distance range mentioned.

We further present collaborative evidence from news articles in support of the channels of strategic cleaning. First, some local governments have targeted air pollution near the ground monitors for strategic intervention using water or water vapor. Since the monitor locations are well known by local officials, they sometimes sprayed water in adjacent areas or targeted fog cannons at the monitors (a high-risk yet effective approach) or toward other subjects near the monitors (lower risk, but less effective). As a case in point, in January 2018, it was reported that the Environmental Protection Agency's office building in Shizhuishan, a city of Ningxia Province, where a central monitor is located, was turned into an "ice sculpture" after being targeted by fog cannons.[1] The next set of

[1]Source: CCTV (2018).

strategies involves various traffic restriction policies targeted at the monitored areas. An official report by Tianjin's environmental inspection team documented the strategic use of temporary traffic control plans by the local agency.[2] The media also reported incidents in which the gas stations near the monitors in Pingdingshan City were temporarily shut down, again a carefully calibrated approach taken by the local government to improve air quality in the immediate area around the monitors.[3] A longer-term strategy was to shut down major sources of pollution to unmonitored suburban areas.[4]

EXAMPLES OF GOVERNMENT DOCUMENTS ON STRATEGIC CLEANING. — **1.Spraying Water**

标题：白银市人民政府办公室关于印发白银市大气污染防治 2017 年度实施方案的通知
文件号：市政办发〔2017〕39 号
发文日期：2017 年 3 月 27 日
相关内容： 3.全面落实扬尘管控措施

（12）加大道路扬尘防治力度，全面落实道路洒水喷雾降尘作业，对重点路段，**特别是两个监测点周边一公里区域内**，要增加洒水频次，保持路面湿润。在沙尘天气开始前和结束后，要全方位进行洒水喷雾降尘。白银区在东南西北城市出入口开展环境卫生治理工作，选取合理位置设置洗车点，禁止施工车辆带泥上路，同时对出入口易起尘路段，采取洒水降尘，建立绿化带、全面清理路旁垃圾、定期保洁等措施有效解决扬尘污染问题。（白银区政府负责，实施时限：全年）

Title: Notification on the Issuance of the Implementation Plan for the Prevention and Control of Air Pollution in Baiyin City in 2017 by the Office of the People's Government of Baiyin City
Document Number: Municipal Office [2017] No. 39
Issue Time: 2017.03.27
Related Content: 3. Comprehensive Implementation of Dust Control Measures (12) Enhance the efforts in dust control on roads, **fully implement road sprinkling and spraying operations to reduce dust, especially within a one-kilometer radius around two monitoring stations,** and increase the frequency of sprinkling to keep the road surface moist. Before and after sand and dust weather events, carry out comprehensive sprinkling and spraying to reduce dust. Baiyin District will conduct environmental sanitation management work at the entrances and exits of the city in the southeast, northwest, and other directions. Reasonable locations will be selected for car washing points, and

[2]See "The Central Environmental Protection Supervision Team: A short-cut plan to guarantee good air quality is set up around the Tianjin Monitoring Station" (dated on July 29th, 2017) for an example. Source: The Paper (2017).

[3]See news and media coverages of the existing manipulation strategies by Chinanews (2018), and The Economic Daily (2015) for more details.

[4]See "Linfen Data Falsification Case: One Year Later, Part of Shanxi's Environmental Information Still Undisclosed" (dated May 10, 2019) for an example. Source:Sina (2019) .

construction vehicles carrying mud will be prohibited from the roads. Additionally, measures such as sprinkling to reduce dust, establishing green belts, comprehensive roadside garbage cleaning, and regular cleaning will be implemented to solve the problem of dust pollution effectively. (Responsibility: Baiyin District Government, Implementation timeframe: Full year)

2.Ban the Coal-fired boiler/ polluted firms and Spray Water

标题：徐州市人民政府关于印发徐州市 2014 年大气污染防治工作任务分解方案的通知
文件号：徐政发〔2014〕47 号
发文日期：2014 年 7 月 17 日
相关内容：38. 对市区 7 个空气质量监测站点**周边 1 公里范围**内全面取缔燃煤锅炉、露天烧烤，餐饮企业符合环保要求，推行立体式绿化和喷淋措施，加强交通疏导，推行湿法保洁，减少二次扬尘和机动车排气污染。

Title: Notification on the Issuance of the Task Decomposition Plan for the Prevention and Control of Air Pollution in Xuzhou City in 2014 by the People's Government of Xuzhou City
Document Number: Xu Zhengfa [2014] No. 47
Issue Time: 2014.07.17
Related Content: 38. **Completely ban coal-fired boilers and open-air barbecues within a one-kilometer radius around seven air quality monitoring stations in the urban area.** Encourage catering enterprises that meet environmental protection requirements to implement three-dimensional greening and sprinkler measures, strengthen traffic diversion, promote wet cleaning, and reduce secondary dust and vehicle exhaust pollution.

3.Vehicle Restriction

标题：吉安市人民政府办公室关于印发《吉安市中心城区油烟污染专项整治行动方案》《吉安市机动车排气污染专项整治行动方案》的通知
发文日期：2017 年 7 月 11 日
相关内容：（五）科学组织货车绕行、禁行。制定**国控监测点周边 3 公里范围**内主要道路货车禁行、限行管控方案，规定禁行、限行区域、时段和车型，并设置标志。对过境市中心城区的重型货运车辆实施远端绕行，禁止穿越主城区。对参与城市建设的水泥罐车、渣土运输车、专项作业车等工程车，严格限制运行时间和路线；对关乎民生的保障货车，公安交管部门对车辆进行严格审批，按照"避开高峰，远离中心，夜间进入"的原则，核准通行时间路线。

Title: Notification on the Issuance of the Special Action Plan for the Control of Cooking
Issue Time: 2017.07.11
Related Content: Oil Fume Pollution in the Central Urban Area of Ji'an City and the Special Action Plan for the Control of Motor Vehicle Exhaust Pollution in Ji'an City by the Office of the People's Government of Ji'an City

(5) Organize the diversion and prohibition of trucks in a scientific manner. **Develop control plans for the prohibition and restriction of trucks on major roads within a 3-kilometer radius of the central stations.** The plans will specify prohibited and restricted areas, time periods, and vehicle types, and appropriate signage will be installed. Heavy-duty freight vehicles passing through the central urban area will be required to take detours at remote locations, and crossing the main urban area will be strictly prohibited. Cement tankers, construction waste transporters, and specialized vehicles involved in urban construction will be subject to strict limitations on operating time and routes. For freight vehicles related to public livelihood, the Public Security Traffic Management Department will conduct a rigorous vehicle approval process, following the principles of "avoiding peak hours, staying away from the city center, and entering during nighttime" to approve the designated times and routes for passage.

4.Ban Open-Air Barbecues

标题：贵阳市人民政府关于印发贵阳市 2015 年大气污染防治工作方案的通知
文件号：筑府发[2015]26 号
发文日期：2015 年 6 月 23 日
相关内容：(3）加强夜市烧烤摊点规范管理。着重整治露天烧烤，严格限制和规范建城区露天烧烤，重点依法取缔**空气自动监测站点周边 1 千米范围内**无组织排放烧烤点。

Title: Notification on the Issuance of the Work Plan for the Prevention and Control of Air Pollution in Guiyang City in 2015 by the People's Government of Guiyang City
Document Number: Zhu Fu Fa [2015] No. 26
Issue Time: 2015.06.23
Related Content: (3) Strengthen the standardized management of night market barbecue stalls. Place a special emphasis on regulating open-air barbecues and strictly restrict and regulate open-air barbecues in the urban area. **Particularly, take decisive actions to prohibit unregulated emission of pollutants from barbecue sites within a one-kilometer radius of automatic air monitoring stations.**

A2. Additional Data Details and Robustness Checks

SATELLITE-BASED $PM_{2.5}$ DATA. — Our main dependent variable is the annual AOD-based $PM_{2.5}$ data compiled by Van Donkelaar et al. (2016). We note, however, that the monthly level data were also made available in a more recent data release by Van Donkelaar et al. (2021).

As detailed in the reference, annual and monthly ground-level fine particulate matter ($PM_{2.5}$) for 1998–2021 were estimated by combining Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWIFS instruments with the GEOS-Chem chemical transport model, and subsequently calibrating to global ground-based observations using a Geographically Weighted Regression (GWR). Meanwhile, raw satellite AOD data are available at the daily level, but their temporal resolution largely depends on satellite coverage. For example, the NASA MODIS instrument collects AOD data every 1 to 2 days from two satellites, Terra and Aqua, which only record AOD on cloud-free days and are sensitive to light surfaces and other weather conditions, leading to missing values at the daily or even weekly level.

Here we assess the pros and cons associated with more- and less-aggregated data. In particular, we examine the correlation between ground-based and AOD-based $PM_{2.5}$ data at the annual and monthly levels, respectively. As shown in Figure A2, there appears to be a stronger correlation at the annual level. This is possibly due to the fact that satellite-based $PM_{2.5}$ measures are subject to idiosyncratic measurement errors from time to time, such as cloud covers, light interference, and other temporal meteorological variations, but can be smoothed out over longer time periods.

Relatedly, we also assess the quality of satellite-based PM data by checking the correlation between AOD-based and ground-based pollution measures before and after automation. However, note that monitoring stations in China only recorded PM_{10}, not $PM_{2.5}$ prior to automation, so we could only investigate the correlation between AOD-based $PM_{2.5}$ and ground-based PM_{10} throughout the sample period. As shown in Figure A3, the correlation becomes strong after automation. We interpret it as evidence of data quality change: PM_{10} data before automation were subject to tampering and were not reliable, as documented by (Greenstone et al., 2022). Automation has improved the accuracy and reliability of ground station data.

ROBUSTNESS CHECKS TO ADDRESS SATELLITE-BASE $PM_{2.5}$ MEASUREMENT ERRORS. —

USING RAW AOD DATA. — As discussed above, the AOD-based $PM_{2.5}$ data were derived from raw satellite images, and the calibration procedure also required information from ground-based monitoring stations. Specifically, the Geographical Weighted Regression method assigns larger weights to areas closer to ground monitors and smaller weights to areas that are farther away. One might worry that the resulting measurement errors are correlated with the distance to monitors and could also be systematically linked to the establishment of new ground monitors. Beyond the validation evidence in Section 3, we conduct our own analysis with raw AOD measurements as an alternative outcome indicator. The pertinent results are reported in Table A2 and Figure A4. Reassuringly, they are largely consistent with the baseline estimates.[5]

USING SATELLITE-BASED POLLUTION MEASURES AT FINER TEMPORAL VARIATION. — We further explore the potential aggregation bias, also known as the "ecological fallacy", associated with annual data (Banzhaf, Ma and Timmins, 2019). To this end, we re-run

[5]The estimated coefficients are smaller with AOD as the outcome, largely because the raw satellite images are sensitive to meteorological conditions (e.g., cloud coverage). In the case of extreme conditions such as haze and fog events, which tend to be associated with heavily-polluted time periods and regions, AOD data may be missing or become unreliable. Thus, without considering such spatial and temporal meteorological variations, the annual average effect estimated from the daily AOD observations (which partially average out) is likely to be small.

analyses on monthly AOD-based $PM_{2.5}$ data and other monthly moments (the maximum and minimum value of daily observations in a month) of raw AOD data.

In order to assess the relevance of aggregation bias, consider the daily regression form of Equation (1) below:

$$(1) \qquad \ln(PM_{2.5icdt}) = \alpha Auto_{ct} + \beta Near_i \times Auto_{ct} + \gamma X_{ct} + Cell_{id} + Year_t + \varepsilon_{ict}$$

Where i and c denote the cell and the city, as previously defined; d denotes the day, and t denotes the year. Aggregating the daily regression to the yearly level means that we can no longer control for the cell-by-day-of-year-fixed effects (Cell $\times$ day of the year), which essentially capture location-specific within-year daily or seasonal patterns of pollution– for example, cells near a factory would be polluting during working days, especially in the summer, but not during weekends. Because of this distinction, estimation biases would arise in the aggregated vis-à-vis disaggregated level when these within-year daily patterns differ (non-causally) before and after automation. We conduct our own analysis to partially evaluate the extent of this omission. In particular, we use a variant of Equation (1) that is based on monthly data. We then estimate β with and without the inclusion of cell-by-calender-month fixed effects ($Cell_{id}$). The results are reported in Table A3 (also in Figure A5, and ring analysis are shown in Figure A20). As shown, they are consistent with our baseline estimates obtained using the annual data, as reported in Table 2. The estimated β with our preferred specification (Column 5) is -0.025, compared to -0.032 in the baseline specification.

Another issue about analyses based on the annual data is that temporal aggregation might discard information: it averages out the rich variation in the heterogeneity of β across clean and dirty days. The same average treatment effect at the aggregated level could represent very different compositions of individual treatment effects across different days. And the different compositions might entail different welfare implications. Just to take one example (conceptually), if local governments attempted to reduce pollution during clean days but increase pollution during dirty days, the resulting health costs could be much greater than those if pollution was reduced during dirty days and increased during clean days, even though the annual average change in pollution levels remained the same under these two scenarios. To shed light on the potential distributional effects, we collect daily raw AOD data, which is the highest resolution possible, and collapse them to the monthly level. This allows us to obtain monthly summary statistics, including the mean, maximum, and minimum values, which can offer a deeper understanding of the within-month distributional response to automation. The results are reported in Table A4. Our findings indicate that monitoring station automation reduced the AOD levels across all three measures. However, the largest log-point change was observed for max AOD. This result indicates that automation likely leads to a reduction in pollution across the entire distribution, but with greater strategic cleaning efforts observed around the monitors during extreme pollution days.

BIAS CORRECTION WITH MULTIPLE IMPUTATION. — Lastly, we address measurement errors due to remote sensing by following the lead of Proctor, Carleton and Sum (2023) in utilizing multiple imputation methods to establish the relationship between AOD-imputed $PM_{2.5}$ values and ground-based monitoring data. Specifically, we employ bootstrap sampling to randomly select 70% of the ground-based monitoring data, and then generate the remaining 30% of the sample through multiple imputations for 100 times. We then utilize that sample of 70% original data and 30% imputed observations to perform regression analysis and simulate the relationship between satellite $PM_{2.5}$ values and their corresponding ground-based readings.

Following that, we predict $PM_{2.5}$ values for all grids in our main dataset using the satellite data and the regression model derived in the previous step. Subsequently, we employ the corrected $PM_{2.5}$ values to repeat our baseline regressions. To account for both sample and imputation uncertainty, we repeat the process of random sampling and prediction 100 times. The results are robust, as reported in Appendix Table A5.

HETEROGENEOUS TREATMENT WITH STAGGERED DID. — This section discusses potential biases arising from the traditional two-way fixed effects (TWFE) estimator in a staggered difference-in-differences design. These biases can arise when early treated units are used as control groups for later treated ones, particularly when there are heterogeneous dynamic treatment effects (Goodman-Bacon, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Sun and Abraham, 2021; Callaway and Sant'Anna, 2021).

To address this issue, we first employ a Goodman-Bacon decomposition of the DiD estimation that regresses the pollution gap between monitored and unmonitored areas on the staggered treatment of monitor automation in a city-year panel. Figure A6 plots the average treatment effect against the weight of each of the six 2×2 comparison groups in the present study. It appears that the average effects of the three early versus later treated groups (i.e., Wave 1 vs. 2, Wave 2 vs. 3, and Wave 1 vs. 3) concentrate around -0.003 and are very close to the TWFE estimator of -0.0039. The sum of the weights of all the earlier versus later groups adds up to more than 50%. Of the three later versus earlier treated groups, which tend to introduce biases to the TWFE estimate, the share of Wave 3 versus Wave 1 and that of Wave 3 vs. Wave 2 add up to 26.7% and 10.3%, respectively. Therefore, we exclude monitors treated in Wave 3 from the treated units and repeat the analysis, again using the triple-difference specification and $\ln PM_{2.5}$ concentrations as the outcome variable.[6] The estimation results are presented in Table A6. Specifically, in our preferred specification, Column (3) shows that the triple difference estimator, i.e., the coefficient of (0-3km)×Auto, increases from -0.032 of the baseline to -0.039 and remains statistically significant. The event study result using pre-2015 data is present in Figure A19. In a similar vein, the results on thermal anomalies are reported in Table A7.

In addition, we employ an alternative estimation approach proposed by Callaway and Sant'Anna (2021), which estimates the group-time average treatment effects (ATTgt)

[6]To maximize identification power from the earlier versus later treated comparison, we switch the treatment status of all monitors treated in Wave 3 to untreated in years 2014 and 2015, based on the assumption that treatment effects would not be realized in the first year (most were treated in December 2014). We also drop all the post-2015 observations.

separately for all treatment cohorts (each group/cohort corresponds to units treated in the same period) relative to never-treated or not-yet-treated control units, and aggregates all of them into simpler parameters. Since the method only applies to a DiD setting, we modify our triple-difference model into a DiD specification, using the pollution gap as the outcome variable. As presented in Figure A7, the result is in line with that of our main triple difference analysis: the pollution gap evolves in parallel between the treated and control monitors before the treatment, and drops significantly in the post-treatment period, implying that the observed improvement in air quality around the monitors relative to the entire city is not driven by biases in the TWFE estimators.

VALIDATION OF THERMAL ANOMALIES DATA. — Before proceeding to the empirical specification, we conduct a set of external validation exercises. We start by assessing the geographical correlation between thermal anomalies and polluting activities. To do so, we obtain two lists of major polluting plants: the first is drawn from the MEE's Key Centrally Monitored Polluting Enterprises database, which consists of 1,829 heavily polluting industrial firms. The other composes of 10,491 power plants, sourced from the China Emissions Accounts for Power Plants (CEAP) database. Figure 5 maps the locations of thermal anomalies along with the geographic distribution of those polluting plants. It is clear from the figure that key centrally monitored industrial firms (Panel A) and power plants (Panel B) are always located in spots with observed thermal anomalies, although those industrial firms and power plants are more spatially dispersed. On that basis, we argue that thermal anomalies provide sufficiently comprehensive coverage of major polluting sources. At the extensive margins, Table A8 shows that, for each 10km-by-10km cell, the presence of any thermal anomaly increases the probability of the presence of a polluting plant by 99%. At the intensive margins, Column (2) of Table A9 shows that for the sample of plant sites, a one percent increase in the radiant heat output around each power plant (capturing the rate at which fuel is consumed and smoke emissions released) is associated with a 0.14 percent growth in the satellite-derived $PM_{2.5}$ measures from the plant, confirming the quality of the thermal anomaly data.

We also test if short-run variations in thermal anomalies respond to temporary drastic government measures on pollution. As a case in point, a series of strict emission control policies were adopted in Beijing and the surrounding regions to ensure blue skies during the 2014 Asia-Pacific Economic Cooperation (APEC) summit. Figure A8 presents the time series of two measures of thermal anomalies one month prior to and one month following the summit for the affected region of Beijing, Tianjin, and Hebei. Both indicators dropped sharply preceding the event and picked up immediately after the summit ended. The observed synchronized pattern again highlights the validity of the thermal anomaly measure in measuring temporal variation in local pollution.

RING ANALYSIS WITH THERMAL ANORMALIES. — Figure A9 further reports the impact of monitor automation on thermal anomalies across different distance bins. The estimated magnitudes of the responses of thermal-based industrial activities to automation decrease as the distance from the monitors increases, which is consistent with the uneven pollution reduction pattern documented in Section 4.3. However, the effect appears to be more localized, with the reduction in industrial activities approaching zero at around 20 km away from the monitors, compared to around 100 km for $PM_{2.5}$ reductions. One possible explanation is that the spatial impact of localized shutdowns of industrial sources on pollution could extend tens of kilometers away as pollutants disperse.

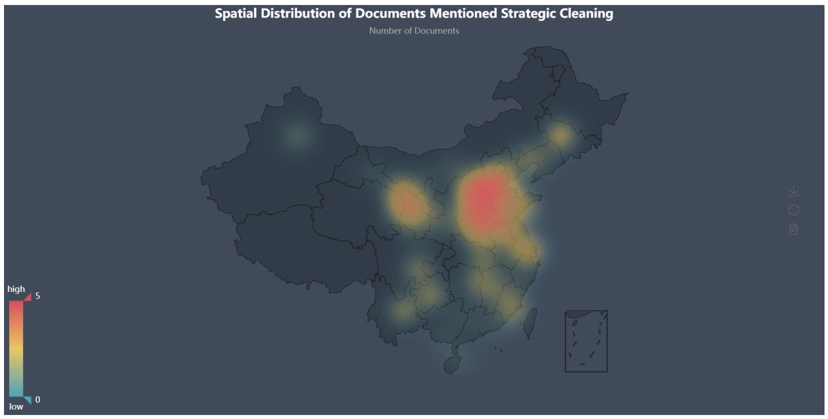
A3. Dynamic Monitor Representativeness

Using fine-scale pollution data and spatial information from the national environmental air monitoring network, we examine the spatial representativeness of these monitors, defined as the difference between the monitor-based and satellite-based city average $PM_{2.5}$. First, we use the 3km by 3km gridded population count from the 2015 National Population Census as the weight for each cell and calculate the weighted average $PM_{2.5}$ for each city. Taking this estimate as the "true" city-level $PM_{2.5}$, we then compare it with the monitor-based population-weighted average $PM_{2.5}$.

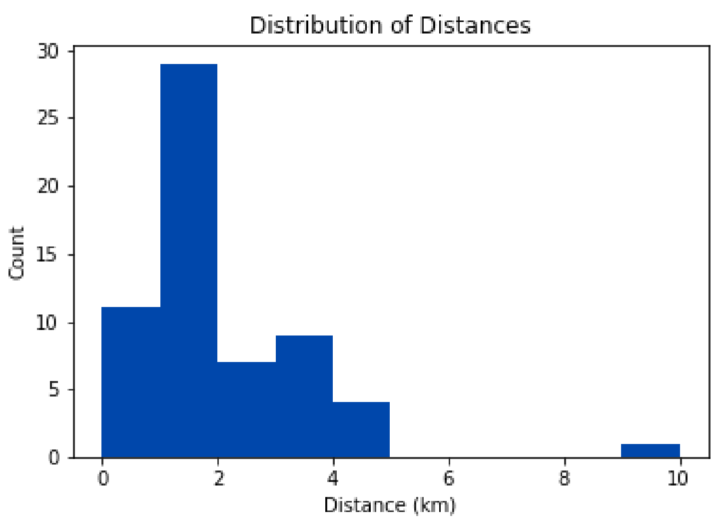
The map in Figure A10 (a) shades cities according to representativeness errors (i.e., how well the monitors capture average air pollution). The blue shading denotes that the monitor under-represents a city's average pollution. At the base year of our study period (i.e., 2008), the monitoring system was indeed fairly representative for most Chinese cities, and monitor locations are unlikely to change once they are placed.[7] However, the spatial representativeness of air quality monitoring is not static but an involving process that can be profoundly shaped by local interventions that target monitored areas. Recall the estimate for the localized pollution reductions in monitored areas: grid cells within a 3km radius of monitors experience a 3.2% greater reduction in $PM_{2.5}$ concentrations than those farther away. Using this central estimate and the last year of the sample period (i.e., 2017), we calculate the projected pollution levels for the five-year period from 2018 to 2022, as shown in Figure A10 (b).[8] The forecast suggests that some previously over-representative monitors seem to move closer to a city's average air quality. However, the most striking result is that monitors in approximately 52 cities are predicted to under-represent overall air pollution by the end of 2022, having been greatly affected by dynamic local strategic conduct.

[7]The current air quality monitors in the U.S. were built two decades ago and covered populated areas following federal guidelines. Other than adding new monitors to counties that did not have them, the existing monitor locations have not changed since then.

[8]We do not extend the extrapolation beyond 2022 because of the large uncertainty and the possibility of new regulations.



(a) Spatial Distribution

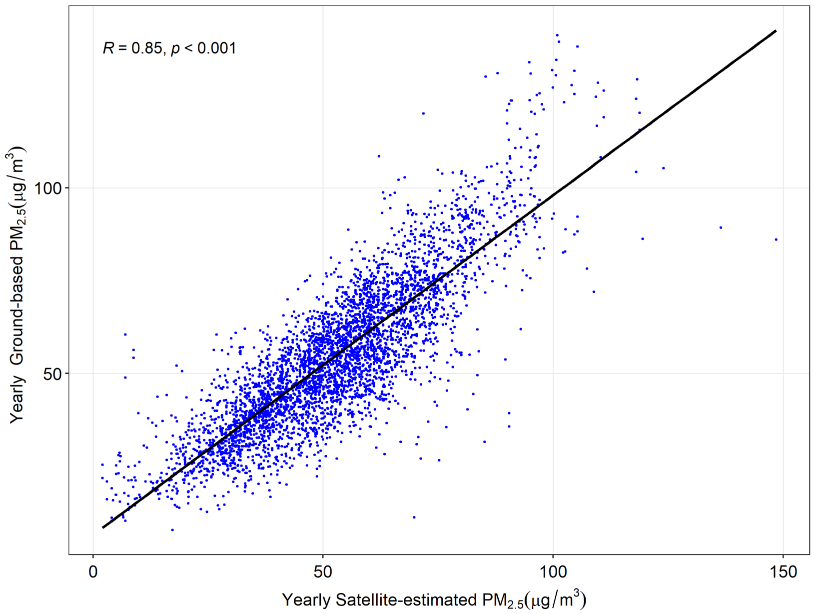


(b) Strategic Cleaning Distance Range

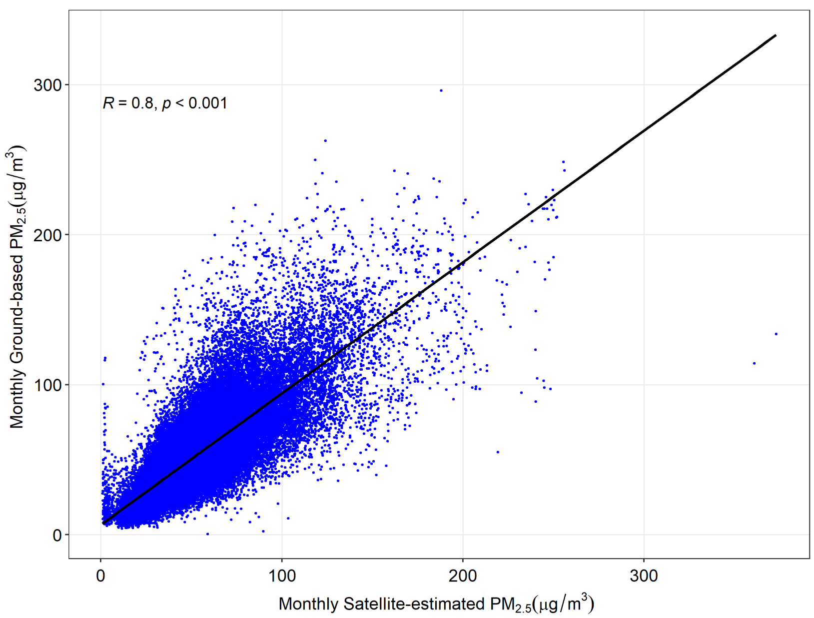
Figure A1. : Government Documents Mentioning "Strategic Cleaning"

Note: Panel A shows the spatial distribution of 121 documents that directly mentioned strategic cleaning around monitors, while Panel B shows the histogram of cleaning range (distance from the monitored) stated in 42 of them.

Figure A2. : Correlation between AOD-based and Ground-based $PM_{2.5}$ Measurements



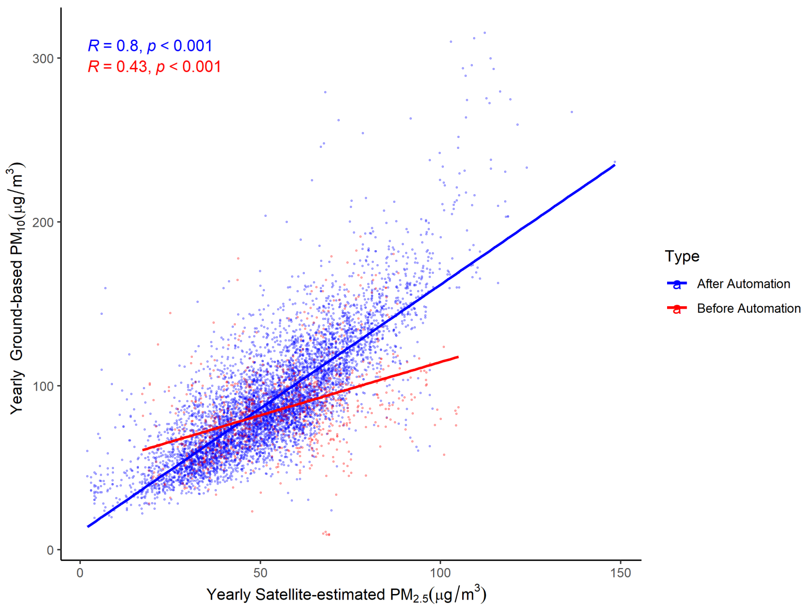
(a) Yearly Data



(b) Monthly Data

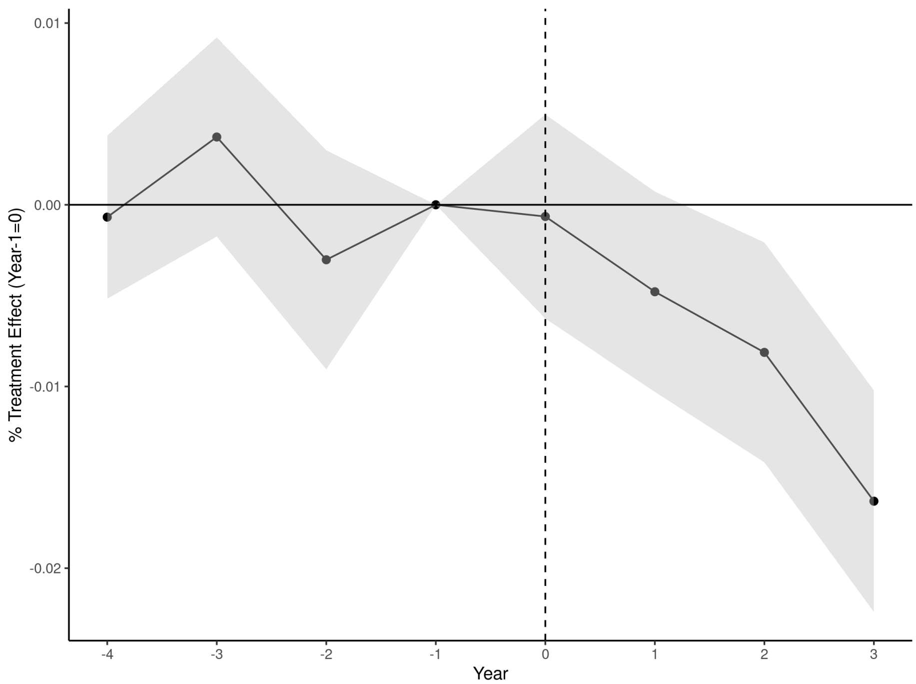
Notes: This figure depicts the correlation between AOD-based $PM_{2.5}$ and ground reading data. Panel A displays the correlation at the yearly level, while Panel B shows the correlation at the monthly level. Ground reading data for $PM_{2.5}$ only became available after automation.

Figure A3. : The Correlation between AOD-based $PM_{2.5}$ and Ground-based PM_{10} Before and After Automation



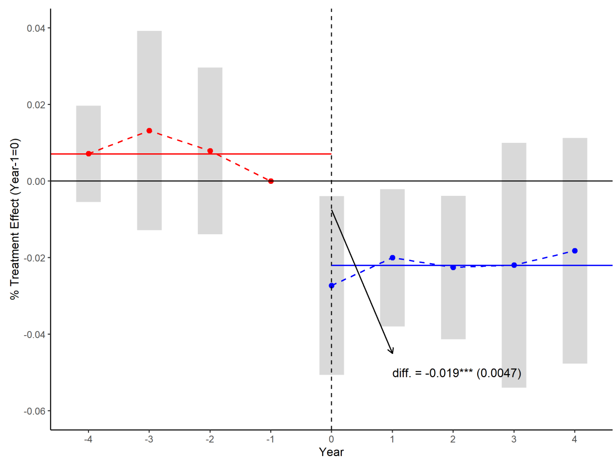
Notes: This figure shows the correlation between yearly AOD-based $PM_{2.5}$ and Ground-based PM_{10} reading data. The red and blue lines represent the fitted linear relationship before and after automation, respectively.

Figure A4. : Robustness Check: Event Study of Monitor Automation, using AOD Raw Data



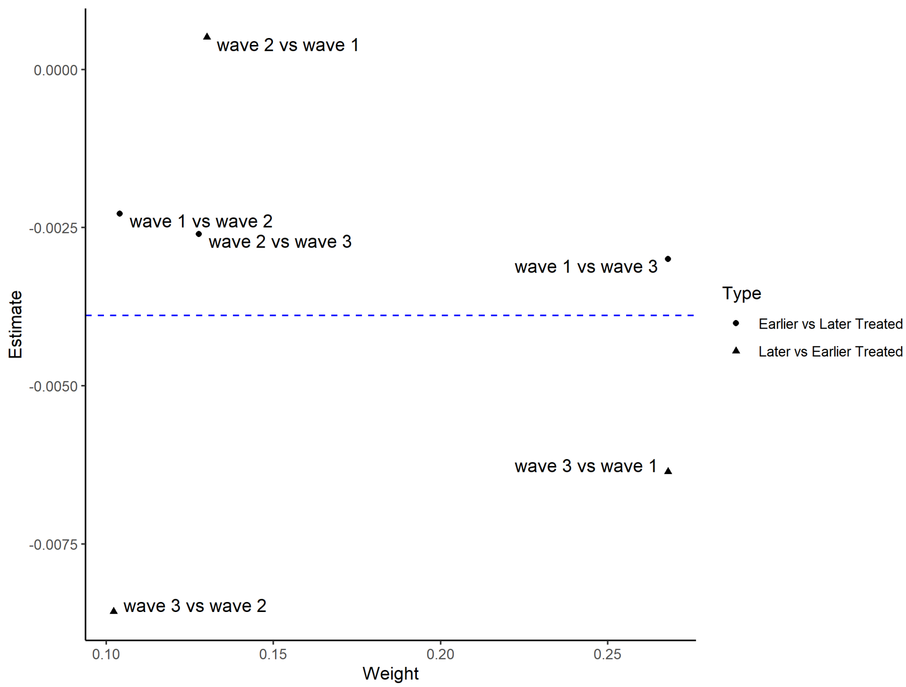
Notes: This figure plots the estimated coefficients and their 95% level confidence intervals for β_n from Equation (3), replacing $PM_{2.5}$ with raw AOD data. Detailed estimates are reported in Table A10. The omitted time category is one year before a city joined the automatic monitoring program. Each estimate represents the difference in ln(AOD) between monitored areas (cells within a 3km radius of a monitor) and unmonitored areas (cells outside a 3km radius around a monitor) at a given period. The regression includes cell fixed effects and year fixed effects, along with flexible interactions between year dummies and an array of pre-treatment city characteristics (such as average GDP, population, $PM_{2.5}$ at the city level from 2008 to 2011, the maximum distance between cells and monitors within a city and a dummy indicator for an environmental priority city), and city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level.

Figure A5. : Event Study: The Effect of Automation on Air Pollution within 3km (Monthly)



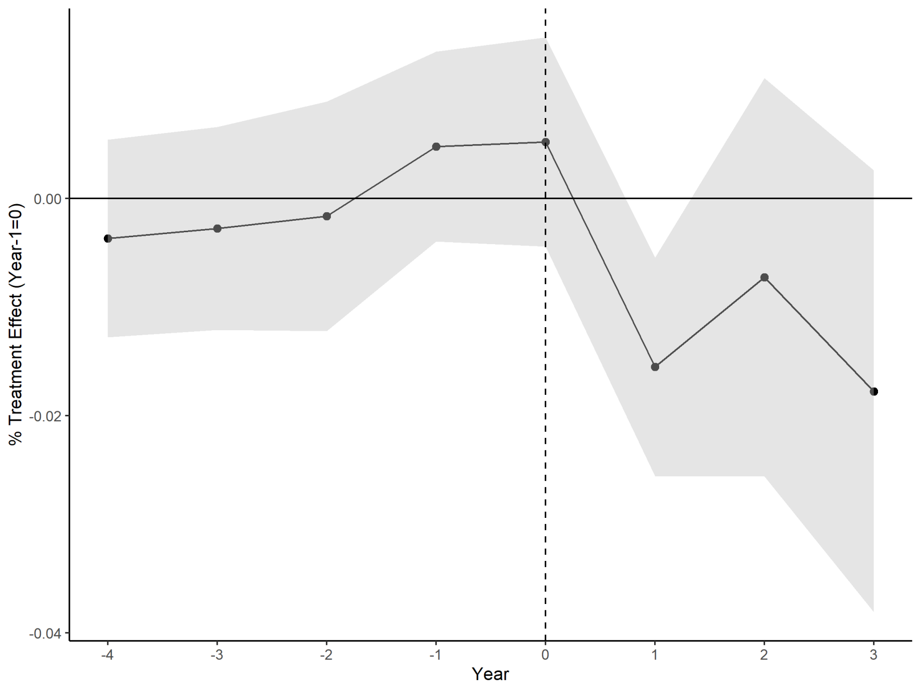
Notes: This figure plots the estimated coefficients and their 95% level confidence intervals for β_n from Equation (3) by using monthly $PM_{2.5}$ Data. Each estimate represents the difference in $PM_{2.5}$ between monitored areas (cells within 3km of monitors) and unmonitored areas (cells outside the 3km radius) at a given period (also reported in Table A3). The omitted time category is the year before a city joined the automated monitoring program. The regression includes cell fixed effects and year fixed effects, along with flexible interactions between year dummies and an array of pre-treatment city characteristics (such as average GDP, population, and $PM_{2.5}$ at the city level from 2008 to 2011, the maximum distance between cells and monitors within a city and a dummy indicator for an environmental priority city), and city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level.

Figure A6. : Robustness Check: Effects of Automation on Pollution Gap of Monitors, Bacon Decomposition for Difference-in-differences



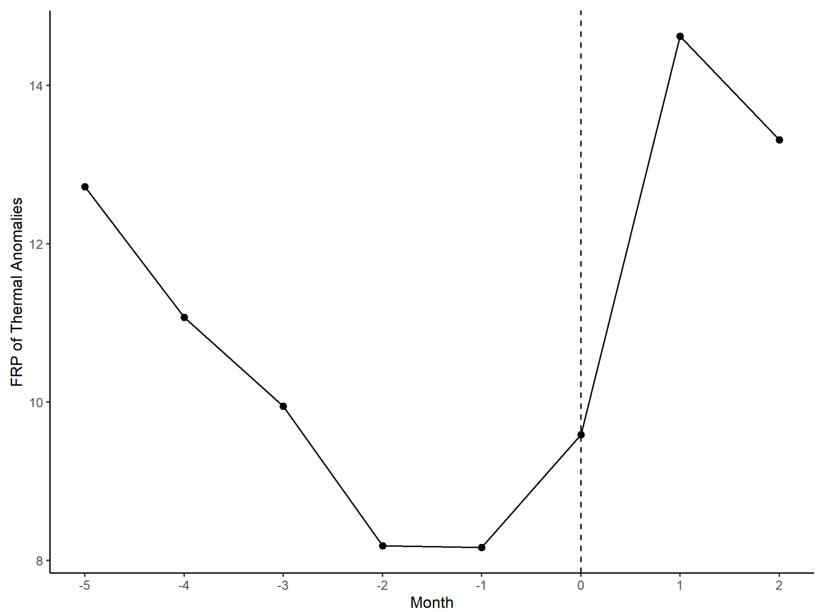
Notes: This figure shows each 2x2 DD estimate from the Bacon decomposition Goodman-Bacon (2021) against their weight for the automation impact analysis. The outcome variable is the pollution gap, defined as the difference between the average pollution within a 3km radius of a monitor and the city's average pollution level. The horizontal dashed line is the difference-in-difference estimate with the pollution gap as the dependent variable (-0.0039 at the 1% significance level). In the Bacon decomposition, the estimate of the "Later vs. Earlier Treated" groups equals -0.0051 and the weights are 0.50.

Figure A7. : Robustness Check: Event Study of Monitor Automation on Pollution Gap, Group-Time Average Treatment Effect Estimation



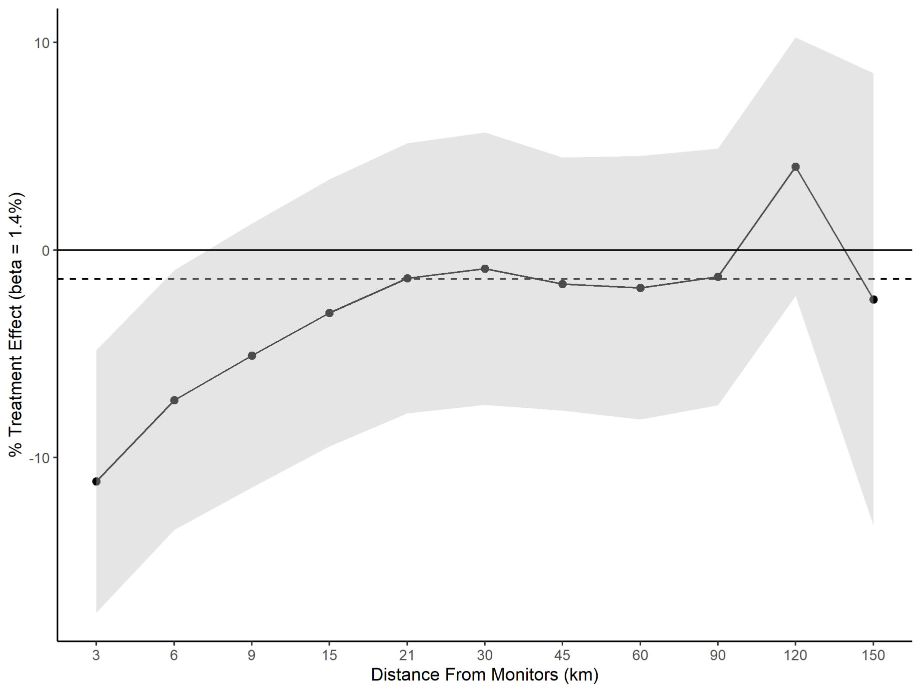
Notes: This figure shows the aggregate event study result following the approach of Callaway and Sant'Anna (2021). The sample includes the period from 2008 to 2015 and sets Wave 3 as the never treated group. The outcome variable is the pollution gap, defined as the difference between the pollution level within 3km of a monitor and the city's average pollution level. All regressions control for cell fixed effects, year fixed effects, and interactions between year dummies and the average city population, and average city-level $PM_{2.5}$ over the 2008–2011 period. Standard errors are clustered at the city level.

Figure A8. : Validation of Thermal Anomalies Using the APEC Event



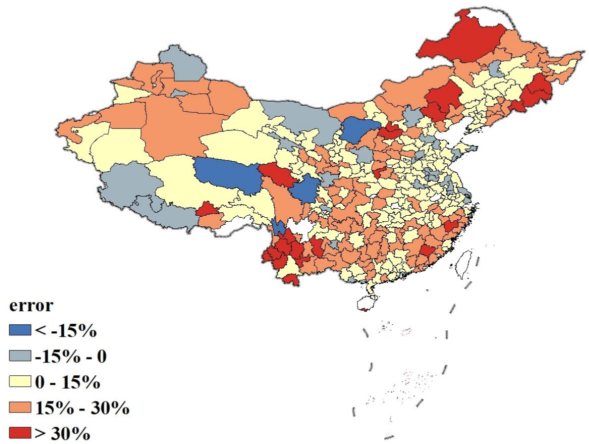
Notes: This figure shows the time series of the thermal anomalies measured shortly before and after the APEC event. Month 0 denotes the month APEC was held (November 2014). FRP is defined as the rate of radiant heat output, which is related to the rate at which fuel is consumed, and smoke emissions are released.

Figure A9. : Effects of Automation on Thermal Anomalies at Different Distances from Monitors

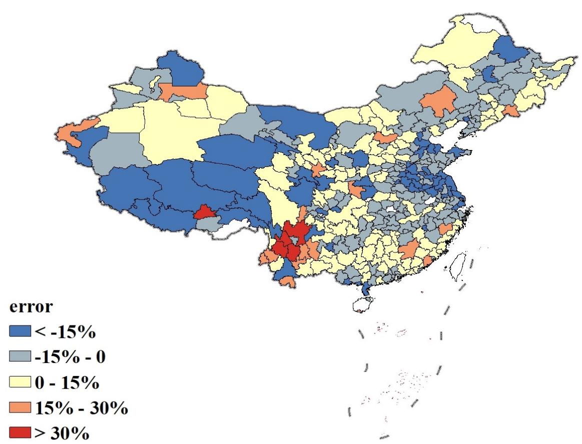


Notes: This figure plots the estimated coefficients and their 95% level confidence intervals for the monitor automation effects on the number of days with active thermal anomalies across different distance bins from the monitor. Each point estimate represents the pollution change in each distance bin relative to the baseline group at the outer range (distance to monitor >150 km), which on average experiences a 1.4% pollution increase. The absolute effect becomes positive above the dotted line. The regression includes cell fixed effects and year fixed effects, along with flexible interactions between year dummies and an array of pre-treatment city characteristics (such as average GDP, population, $PM_{2.5}$ at the city level from 2008 to 2011, the maximum distance between cells and monitors within a city and a dummy indicator for an environmental priority city), and city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level.

Figure A10. : Monitor Representation Errors: All Cells vs. Monitored Cells



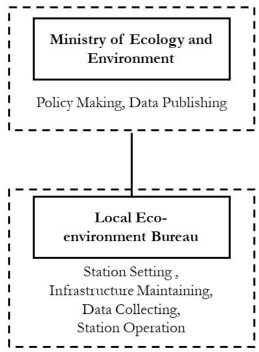
(a) Representation Errors in 2008



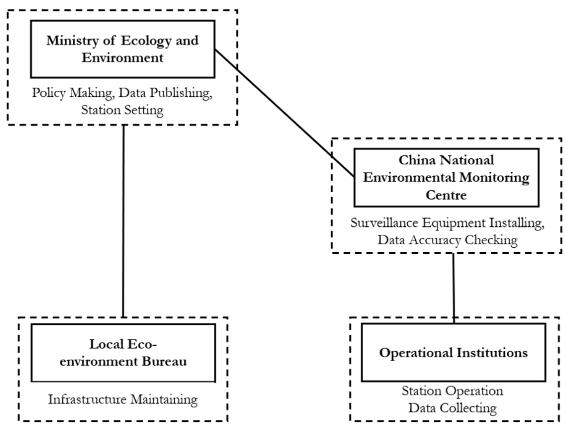
(b) Representation Errors in 2022

Notes: This figure presents the monitor representation errors. Panel A shows monitor representation errors at the base year of the study period (2008). Panel B shows the predicted representation errors of monitors in 2022, which are calculated based on the estimated pollution reductions in monitored areas (cells within a 3km radius of monitors have experienced a 3.2% greater reduction in air pollution relative to unmonitored areas), and are projected beyond the last year of the sample period (2017). The representation error is defined as the percentage difference between the population-weighted, satellite-based average pollution in monitored cells and the average pollution across all cells within the city boundary. Negative measures indicate under-representation by monitors.

Figure A11. : Change in Environmental Authorities' Responsibilities



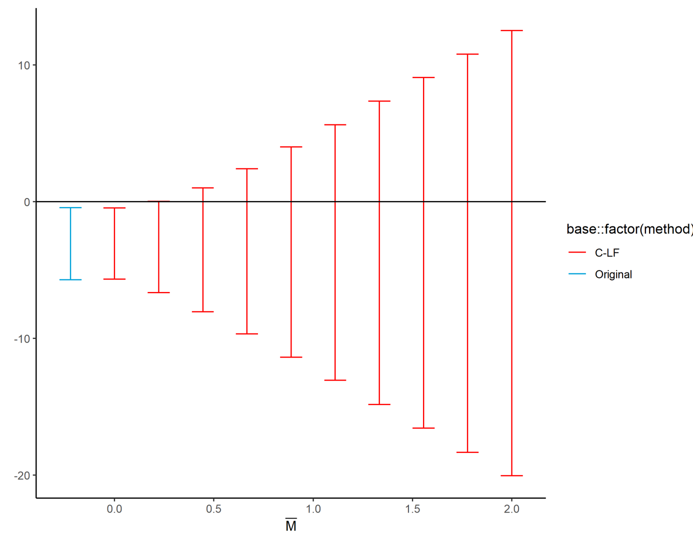
(a) Before



(b) After

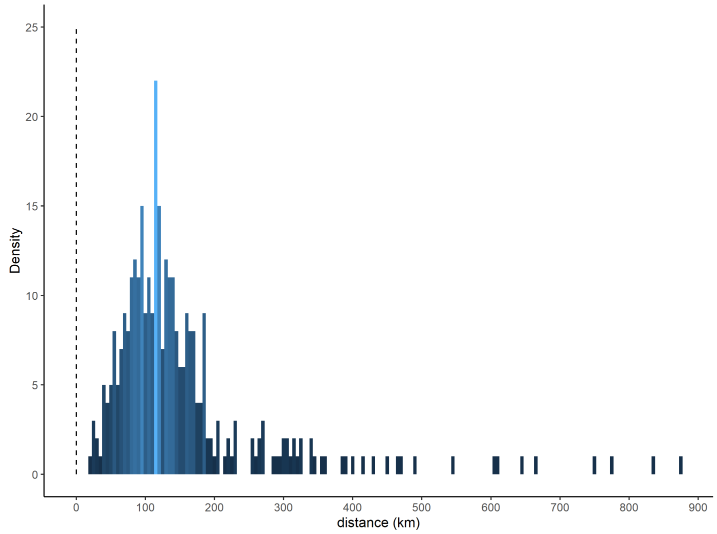
Notes: These two figures illustrate the roles and responsibilities of different environmental authorities, before (Panel A) and after (Panel B) the introduction of new standards. China National Environmental Monitoring Centre (CNEMC) is a newly established institution directly under the management of the Ministry of Environment and Ecology (MEE). It entrusts and oversees several third-party operational institutes to operate and maintain the monitoring stations. Among the various responsibilities, Infrastructure Maintenance refers to ensuring the supply of electricity and communications, and Data Accuracy Checking denotes checking the anomaly data.

Figure A12. : Robust Analysis of Event Study on $PM_{2.5}$



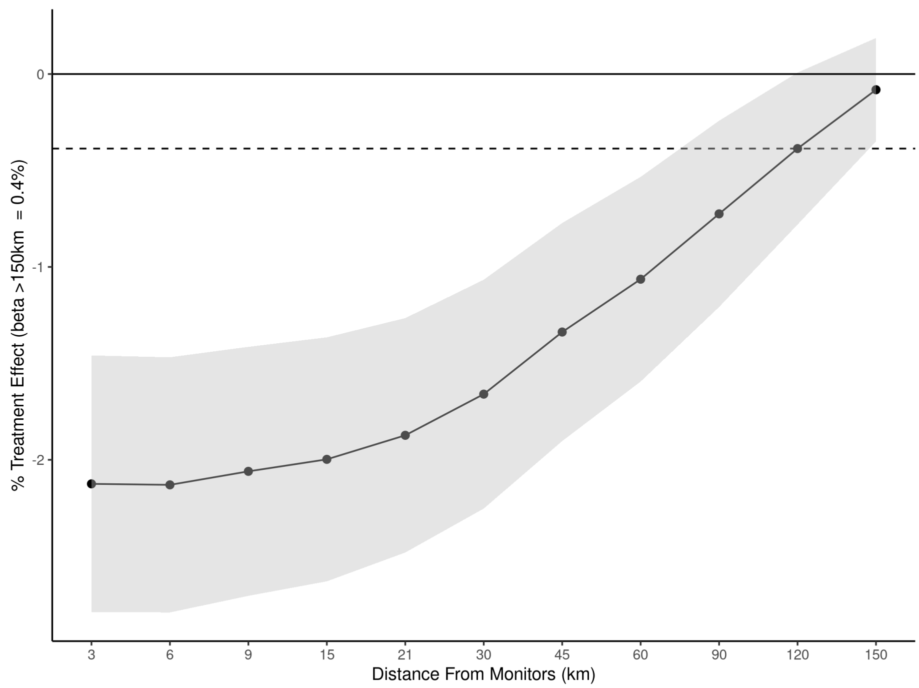
Notes: This figure shows the sensitivity analysis of estimated effects on $PM_{2.5}$ to potential violations of the parallel trends assumption following the methods proposed by Rambachan and Roth (2019). The blue bar represents the 95% confidence interval of the DiD estimate for the last period ($\tau = 3$) from the estimation of Equation (3). The red bars represent corresponding 95% confidence intervals when allowing for per-period violations of parallel trends up to M, which is the largest allowable change in the slope of an underlying linear trend between two consecutive periods.

Figure A13. : Cities' Maximum Distance between Cells and Monitors



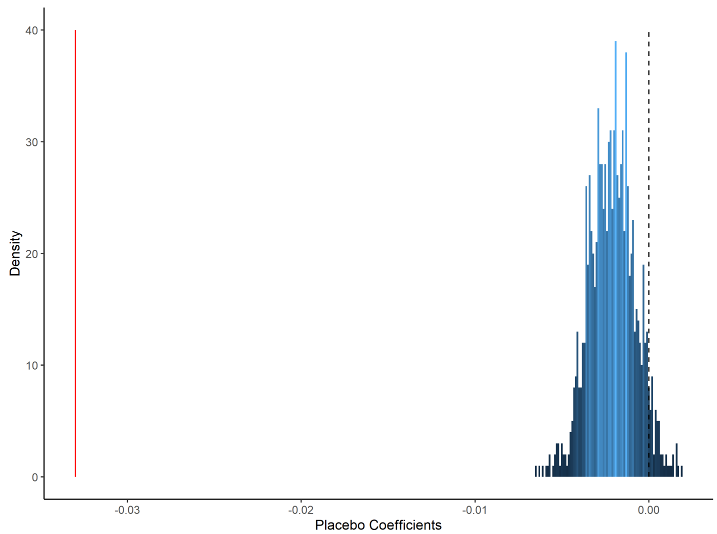
Notes: This figure shows the distribution of the maximum distance between cells and monitors (a proxy for city's geographical size) across cities. The maximum distance ranges from 18 km to 873 km, and the average maximum distance is 152 km.

Figure A14. : Robustness Check: Effects of Automation on ln(AOD) across Distances from Monitors

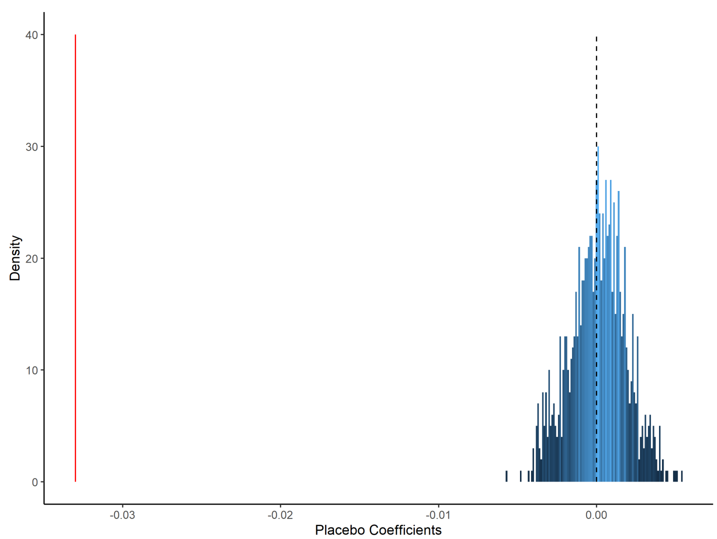


Notes: This figure plots the estimated coefficients and their 95% level confidence intervals for the effects of monitor automation on the satellite-based ln(AOD) at different distance bins from the monitor. Each point estimate represents the pollution change in each distance bin relative to the baseline group at the outer range (distance to monitor $>$150 km), which on average experiences a 0.4% pollution increase. The absolute effect becomes positive above the dotted line. The regression includes cell fixed effects and year fixed effects, along with flexible interactions between year dummies and an array of pre-treatment city characteristics (such as average GDP, population, $PM_{2.5}$ at the city level from 2008 to 2011, the maximum distance between cells and monitors within a city and a dummy indicator for an environmental priority city), and city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level.

Figure A15. : Placebo Tests: Randomizing Treatment Timing and Locations



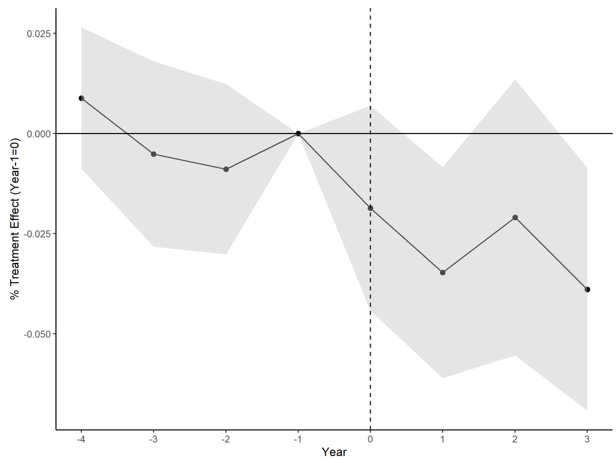
(a) Random Automation Years



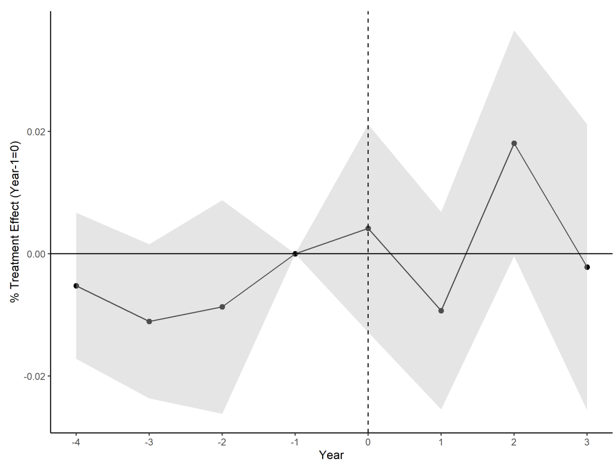
(b) Random Monitor Locations

Notes: This figure presents the results of two placebo tests (See Equation (1)). Figure (a) plots a "placebo" test that randomly assigns each monitor an automation year within the sample period from 2008 to 2017. Figure (b) plots a "placebo" test that randomly assigns monitor sites to various locations while keeping the number of monitors and the year of automation unchanged. For each placebo test, the DiD estimation is repeated 1000 times. The distribution of the estimates from the 1000 runs (blue lines) is then plotted along with the benchmark estimate (red line).

Figure A16. : Event Study: The Effect of Automation on Air Pollution within 3km Across Different Types of Monitors



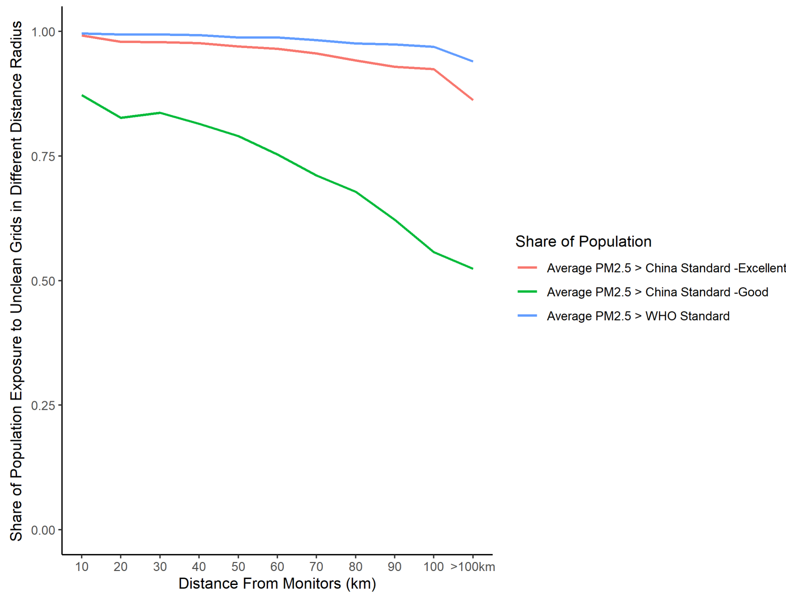
(a) Regional Assessing Monitors



(b) Background Monitors

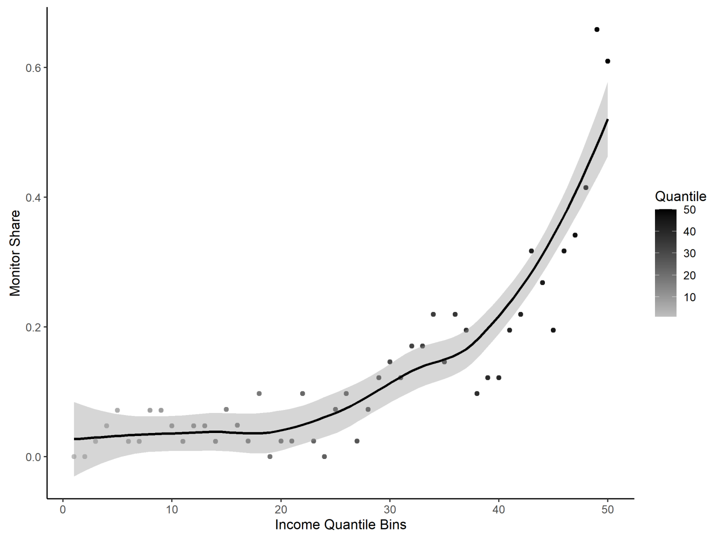
Notes: This figure plots the estimated coefficients and their 95% level confidence intervals for β_n from Equation (3) by different types of monitors (Minitry of Ecology and Environment, 2013). Panel A uses regional assessing monitors that are used to measure a city's pollution level. Panel b uses background stations that are placed far away from pollution sources and urban areas to serve as a reference. Each estimate represents the difference in $PM_{2.5}$ between monitored areas (cells within 3km of monitors) and unmonitored areas (cells outside the 3km radius) at a given period. The omitted time category is the year before a city joined the automated monitoring program. The regression includes cell fixed effects and year fixed effects, along with flexible interactions between year dummies and an array of pre-treatment city characteristics (such as average GDP, population, and $PM_{2.5}$ at the city level from 2008 to 2011, the maximum distance between cells and monitors within a city and a dummy indicator for an environmental priority city), and city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level.

Figure A17. : Share of the Population Exposed to Unhealthy Pollution Levels at Different Distances from Monitors

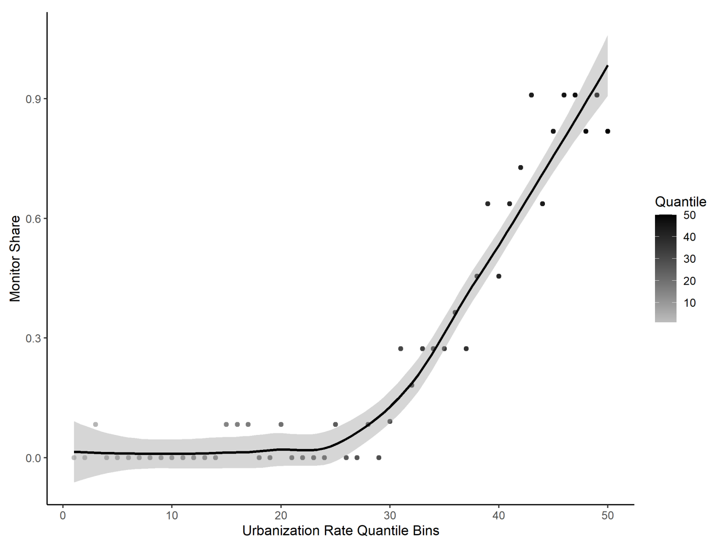


Notes: This figure displays the proportion of the population exposed to unhealthy levels of pollution at varying distances from the monitoring stations. The exposure to unhealthy levels of pollution is defined as residing in grid cells where the concentration of PM2.5 exceeds the established air quality standards–The World Health Organization (WHO) recommends a standard of 10 ug/m^3, while China specifies good air quality as 35 ug/m^3 and excellent air quality as 15 ug/m^3. To infer the health threshold of AOD-based $PM_{2.5}$ from the 10/15/35 ug/m3 standards with the ground monitoring data, we follow a two-step process. Firstly, we establish the relationship between AOD-imputed $PM_{2.5}$ and ground-based $PM_{2.5}$ using a regression model. Secondly, we pin down the AOD-based $PM_{2.5}$ levels when ground-based $PM_{2.5}$ takes on the value of 10/15/35 ug/m3.

Figure A18. : Uneven Distribution of Air Quality Monitors Across Counties



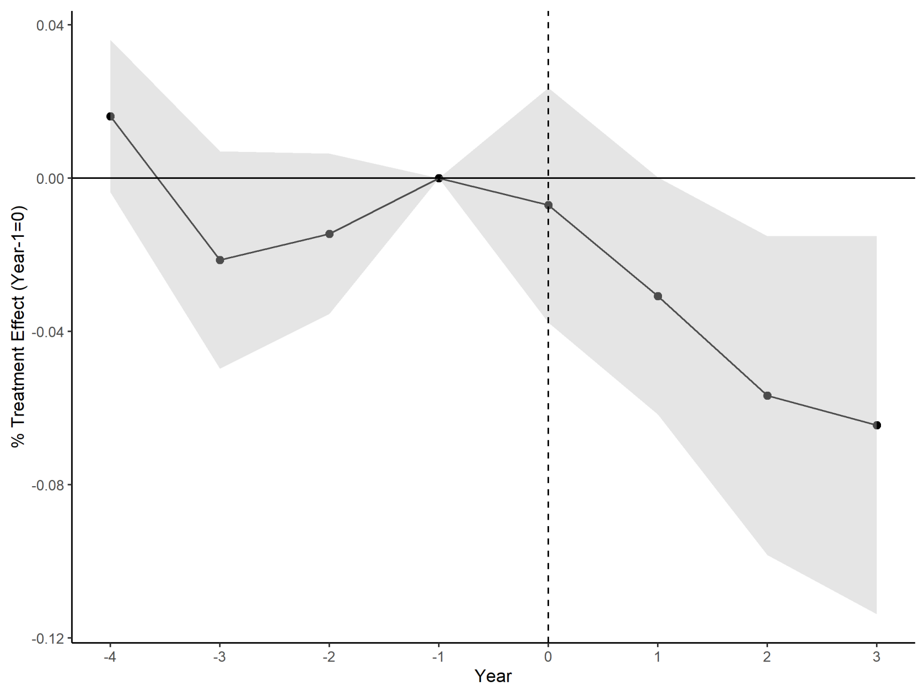
(a) By Income



(b) By Urbanization Rate

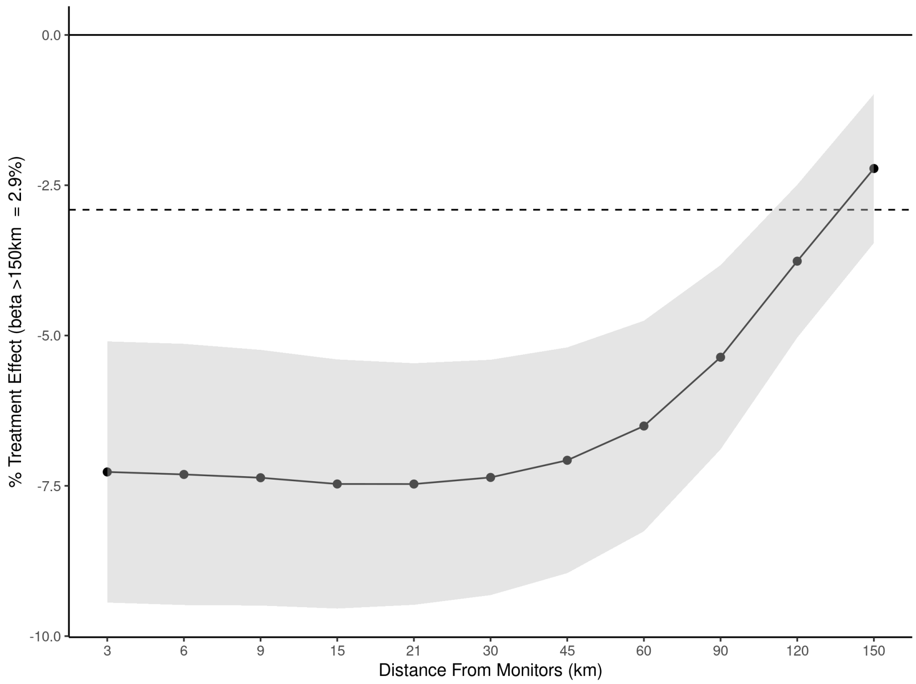
Notes: This figure presents the monitor share across quantiles of counties. Panel A divides counties into 50 groups according to their GDP per capita during the pre-policy period (before 2012). Panel B categorizes counties into 50 groups based on their urbanization rate. The monitor share is defined as the percentage of counties with air quality monitors within their corresponding groups.

Figure A19. : Event Study: The Effect of Monitor Automation on Air Pollution within 3km of a Monitor (2008–2015)



Notes: This figure plots the estimated coefficients and their 95% level confidence intervals for β_n from Equation (3). This figure depicts the periods from 2008 to 2015 and sets the sample in Wave 3 as the never treated group. Each estimate represents the difference in $PM_{2.5}$ between monitored areas (cells within 3km of monitors) and unmonitored areas (cells outside 3km) at a given period. The omitted time category is the year before a city joined the automatic monitoring program. The regression includes cell fixed effects and year fixed effects, along with flexible interactions between year dummies and an array of pre-treatment city characteristics (such as average GDP, population, $PM_{2.5}$ at the city level from 2008 to 2011, the maximum distance between cells and monitors within a city and a dummy indicator for an environmental priority city), and city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level.

Figure A20. : Effects of Automation on $\ln PM_{2.5}$ at Different Distances from Monitors (Monthly)



Notes: This figure plots the estimated coefficients and their 95% level confidence intervals for the effects of monitor automation on the satellite-based $\ln PM_{2.5}$ at different distance bins from the monitor by using Monthly AOD-based $PM_{2.5}$ data. Each point estimate represents the pollution change in each distance bin relative to the baseline group at the outer range (distance to monitor >150 km), which on average experiences a 2.9% pollution increase. The absolute effect becomes positive above the dotted line. The regression includes cell fixed effects and year fixed effects, along with flexible interactions between year dummies and an array of pre-treatment city characteristics (such as average GDP, population, $PM_{2.5}$ at the city level from 2008 to 2011, the maximum distance between cells and monitors within a city and a dummy indicator for an environmental priority city), and city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level.

Table A1—: Key government policy documents about Air Pollution Prevention during 2013–2017

Policy Name	Short Name	Issue Time
Action Plan for Air Pollution Prevention and Control	Air Ten	2013.09
Target Responsibility Agreement (mubiao zerenshu) for Atmospheric Pollution Prevention and Control	Target	2013.10
Notice of the General Office of the State Council on Performance Assessment Measures for Air Pollution Prevention and Control Action Plan	Assessment	2014.04

Notes: This table shows the key government policy documents on air pollution prevention and performance assessment during 2013–2017 and their issuing time. All are issued by the Ministry of Ecology and Environment (MEE) in China.

Table A2—: Robustness Check: Localized Cleanup Response to Monitoring Program Automation, using AOD Raw Data

	Dependent variable: ln(AOD)			
	(1)	(2)	(3)	(4)
Unmonitored Areas:	>3km	>3km	>3km	>60km
Auto	-0.0044	0.0024	-0.0044	-0.0053*
	(0.0027)	(0.0027)	(0.0027)	(0.0031)
(0-3km)×Auto		-0.0198***	-0.0090***	-0.0180***
		(0.0028)	(0.0016)	(0.0032)
CellFE	X	X	X	X
Year FE	X	X	X	X
Year FE × citypopulation$^{2008-2011}$	X		X	X
Year FE × $PM_{2.5}^{2008-2011}$	X		X	X
Year FE × Other City-level Controls	X		X	X
Concurrent Policy	X		X	X
Observations	10,865,784	10,888,044	10,865,784	7,399,416
R^2	0.945	0.930	0.945	0.934

Notes: This table reports the effects of the monitor automation program on the satellite-based ln(AOD). Auto is the treatment indicator that switches on after a city has joined the automatic monitoring program. (0-3km) is a dummy variable that equals one if the cells are located within a 3km radius of a city's monitoring stations. Columns (3) and (4) use cells within 3km of a monitor as the monitored group and compare them with different unmonitored groups: cells outside 3km and 60km of the monitors. $PM_{2.5}^{2008-2011}$ is the average city-level $PM_{2.5}$ and citypopulation$^{2008-2011}$ is the average city population over the 2008–2011 period. Other city-level controls include the average city-level GDP between 2008 and 2011, the number of monitors for each city, the maximum distance between cells and monitors within a city, and a dummy variable that indicates whether or not a city is an environmental priority city. The Concurrent Policy refers to the city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level. Significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A3—: Localized Cleanup Response to Monitor Automation (Monthly)

	Dependent variable: $\ln(PM_{2.5})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Unmonitored Areas:	>3km	>3km	>3km	>3km	>3km	>60km
Auto	0.0164	-0.0203	0.0168	-0.0154	-0.0202	-0.0168
	(0.0116)	(0.0140)	(0.0116)	(0.0115)	(0.0140)	(0.0233)
(0-3km)×Auto			-0.0622***	-0.0302***	-0.0247***	-0.0374**
			(0.0093)	(0.0073)	(0.0079)	(0.0157)
CellFE	X	X	X	X	X	X
Year Month FE	X	X	X	X	X	X
CellFE X Month FE		X		X	X	X
Year FE × citypopulation$^{2008-2011}$		X		X	X	X
Year FE × $PM_{2.5}^{2008-2011}$		X		X	X	X
Year FE × Other City-level Controls		X			X	X
Concurrent Policy		X			X	X
Observations	124,594,942	124,594,942	124,594,942	124,594,942	124,594,942	90,429,709
R^2	0.961	0.962	0.961	0.963	0.956	0.955

Notes: This table reports the effects of the monitor automation program on the satellite-based $\ln PM_{2.5}$. $\ln PM_{2.5}$ is the natural logarithm of the cell-level monthly satellite-based $PM_{2.5}$. Auto is the treatment indicator that equals one after a city has joined the automatic monitoring program. (0-3km) is a dummy variable that equals one if the cells are located within a 3km radius of a city's monitoring stations. Columns (1)–(6) use cells within 3km of the monitor as the monitored group, comparing them with different unmonitored groups: cells beyond 3km from the monitors in columns (1)–(5) and 60km from the monitors in column (6), respectively. $PM_{2.5}^{2008-2011}$ is average city-level $PM_{2.5}$ during the 2008–2011 period and citypopulation$^{2008-2011}$ is the average city population from 2008 to 2011. Other city-level controls are the average city-level GDP from 2008 to 2011, the number of monitors in each city, the maximum distance between cells and monitors within a city, and a dummy variable that indicates whether or not a city is an environmental priority city. The Concurrent Policy refers to the city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level. Significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A4—: Localized Cleanup Response to Monitoring Program Automation: AOD (Monthly)

Dependent variable:	$\ln(AOD^{MonthlyMax})$		$\ln(AOD^{MonthlyMin})$		$\ln(AOD^{MonthlyMean})$	
	(1)	(2)	(3)	(4)	(5)	(6)
Auto	0.0014	-0.0101	-0.00009.33	-0.0028	0.0006	-0.0054**
	(0.0064)	(0.0069)	(0.0023)	(0.0022)	(0.0023)	(0.0025)
(0-3km)×Auto	-0.0372***	-0.0141*	-0.0147**	-0.0093	-0.0278***	-0.0139**
	(0.0096)	(0.0079)	(0.0062)	(0.0059)	(0.0072)	(0.0064)
CellFE	X	X	X	X	X	X
Year Month FE	X	X	X	X	X	X
CellFE X Month FE		X		X	X	X
Year FE × citypopulation$^{2008-2011}$		X		X		X
Year FE × AOD$^{2008-2011}$		X		X		X
Year FE × Other City-level Controls		X		X		X
Concurrent Policy		X		X		X
Observations	114,062,258	113,802,919	114,062,258	113,802,919	114,062,258	113,802,919
R^2	0.684	0.692	0.721	0.726	0.769	0.777

Notes: This table reports the effects of the monitor automation program on the satellite-based lnAOD. We construct different monthly AOD statistics based on the daily AOD data within each month. $\ln(AOD^{MonthlyMax})$ and $\ln(AOD^{MonthlyMin})$ is the natural logarithm of the cell-level maximum and minimum AOD value of each month, and $\ln(AOD^{MonthlyMean})$ is the natural logarithm of the cell-level average AOD value of each month. Auto is the treatment indicator that equals one after a city has joined the automatic monitoring program. (0-3km) is a dummy variable that equals one if the cells are located within a 3km radius of a city's monitoring stations. $AOD^{2008-2011}$ is average city-level $AOD_{\text{MonthlyMax}}$ during the 2008–2011 period and citypopulation$^{2008-2011}$ is the average city population from 2008 to 2011. Other city-level controls are the average city-level GDP from 2008 to 2011, the number of monitors in each city, the maximum distance between cells and monitors within a city, and a dummy variable that indicates whether or not a city is an environmental priority city. The Concurrent Policy refers to the city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level. Significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A5—: Robustness Check: Correction Via Multiple Imputations

Dependent Variable:		$\ln(\text{PM}_{2.5})$	
	(1)	(2)	(3)
Variables			
Auto	0.0250	-0.00989	0.00208
	(0.0147)	(0.0153)	(0.0164)
(0-3km)×Auto	-0.0586***	-0.0247***	-0.0234***
	(0.0112)	(0.00653)	(0.00701)
CellFE	X	X	X
Year FE	X	X	X
Year FE × citypopulation$^{2008-2011}$		X	X
Year FE × $\ln(\text{PM2.5})^{2008-2011}$		X	X
Year FE × Other City-level Controls			X
Concurrent Policy			X
Observations	10,413,717	10,413,717	10,413,717

Notes: This table reports the effects of the monitor automation program on the natural logarithm of the cell-level yearly satellite-based $\ln\text{PM}_{2.5}$ with correction. Following the lead of Proctor, Carleton and Sum (2023), we employ bootstrap sampling to randomly select 70% of the ground-based monitoring data and then generate the remaining 30% of the sample through multiple imputations. We then utilize that sample of the 70% original data, and 30% imputed observations to perform regression analysis and simulate the relationship between satellite $\text{PM}_{2.5}$ values and their corresponding ground-based readings. Following that, we predict $\text{PM}_{2.5}$ values for all grids in our main dataset using the satellite data and the regression model derived in the previous step. This process is repeated 100 times. The parameters presented represent the means calculated from this distribution of bootstrap samples. Auto is the treatment indicator that equals one after a city has joined the automatic monitoring program. (0-3km) is a dummy variable that equals one if the cells are located within a 3km radius of a city's monitoring stations. $\text{PM}_{2.5}^{2008-2011}$ is average city-level $\text{PM}_{2.5}$ during the 2008–2011 period and citypopulation$^{2008-2011}$ is the average city population from 2008 to 2011. Other city-level controls are the average city-level GDP from 2008 to 2011, the number of monitors in each city, the maximum distance between cells and monitors within a city, and a dummy variable that indicates whether or not a city is an environmental priority city. The Concurrent Policy refers to the city-level concurrent PM_{10} and $\text{PM}_{2.5}$ reduction targets. Standard errors are clustered at the city level. Significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A6—: Robustness Check: Localized Cleanup Response to Monitor Automation (2008–2015)

	Dependent variable: $\ln(PM_{2.5})$			
	(1)	(2)	(3)	(4)
Unmonitored Areas:	>3km	>3km	>3km	>60km
Auto	-0.029	-0.002	-0.029	-0.057*
	(0.021)	(0.024)	(0.021)	(0.029)
(0-3km)×Auto		-0.032***	-0.039***	-0.077***
		(0.012)	(0.012)	(0.027)
CellFE	X	X	X	X
Year FE	X	X	X	X
Year FE × $\text{citypopulation}^{2008-2011}$	X		X	X
Year FE × $PM_{2.5}^{2008-2011}$	X		X	X
Year FE × Other City-level Controls	X		X	X
Concurrent Policy	X		X	X
Observations	8,330,086	8,330,086	8,330,086	6,067,588
R^2	0.980	0.977	0.980	0.980

Notes: This table reports the effects of the monitor automation program on the satellite-based $\ln PM_{2.5}$. The sample covers the 2008–2015 period, setting monitors treated in Wave 3 as the never treated ones. $\ln PM_{2.5}$ is the natural logarithm of the cell-level yearly satellite-based $PM_{2.5}$. Auto is the treatment indicator that switches on after a city has joined the automatic monitoring program. (0-3km) is a dummy variable that equals one if the cells are located within a 3km radius of a city's monitoring stations. Columns (3) and (4) use cells within 3km of the monitor as the monitored group and compare it with different unmonitored groups: cells outside 3km and 60km of the monitors, respectively. $PM_{2.5}^{2008-2011}$ is the average city-level $PM_{2.5}$ and $\text{citypopulation}^{2008-2011}$ is the average city population over the 2008–2011 period. Other city-level controls are the average city-level GDP between 2008 and 2011, the number of monitors in each city, the maximum distance between cells and monitors within a city, and a dummy variable that indicates whether or not a city is an environmental priority city. The Concurrent Policy refers to the city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level. Significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A7—: Robustness Check: Mechanism of Localized Cleaning (2008-2015)–Thermal Anomalies

VARIABLES	(1) 1(TAP)	(2) ln(Days+1)	(3) ln(FRP+1)	(4) ln(Days+1)	(5) ln(FRP+1)
Auto	0.336***	-0.0469	-0.0325	0.00160**	0.00329**
	(0.0150)	(0.0414)	(0.0445)	(0.000651)	(0.00150)
Marginal Effect	*0.0839****	*-0.0144*	*-0.0230*		
	(0.00402)	*(0.0127)*	*(0.0315)*		
(0-3km)×Auto	-0.377***	-0.263***	-0.233***	-0.00676	-0.00528
	(0.0589)	(0.0448)	(0.0455)	(0.00558)	(0.0125)
Marginal Effect	*-0.0660****	*-0.0808****	*-0.165****		
	(0.0144)	*(0.0138)*	*(0.0322)*		
Cell FE	X	X	X	X	X
Year FE	X	X	X	X	X
Year FE × citypopulation$^{2008-2011}$		X	X	X	X
Year FE × $PM_{2.5}^{2008-2011}$		X	X	X	X
Year FE × Other City-level Controls		X	X	X	X
Concurrent Policy		X	X	X	X
Model	Logit	Poisson	Poisson	OLS	OLS
Sample	All	All	All	1(TAP)	1(TAP)
Observations	127,288	165,040	165,040	39,125	39,125
R-squared				0.743	0.583

Notes: This table reports the effects of the monitor automation program on thermal anomalies. The analysis uses the sample from 2008 to 2015 and sets monitors automated in Wave 3 as the never treated ones. Column (1) uses a logit regression model. Columns (2) and (3) use a Poisson regression model. Columns (4) and (5) use an OLS model. For the logit and Poisson regression models, the marginal effects are also reported. Column (1) reports the results for a dummy indicator of thermal anomalies presence (TAP), denoted by 1(TAP), which is equal to one if thermal-related economic activities are present in a cell in that year. Column (2) reports the results for the number of days with active thermal anomalies using the full sample, which measures the operating time of industrial plants in each cell. Column (3) reports the results for the average intensity of thermal anomalies, denoted by ln(FRP+1). FRP is defined as the rate of radiant heat output, which is related to the rate at which fuel is consumed, and smoke emissions are released. We use the natural logarithm of (FRP+1) and (Days+1) to tackle zero observations. Column (4) reports the effect of automation on the logarithm of the number of days with active thermal anomalies by restricting the sample to only those grid cell-year observations when 1(TAP) is equal to one. Column (5) reports the effect of automation on the average intensity of thermal anomalies per day (denoted by ln(FRP+1)) when 1(Thermal Anomalies Presence) is equal to one. $\ln PM_{2.5}$ is the natural logarithm of the cell-level yearly satellite-based $PM_{2.5}$. Auto is the treatment indicator that takes the value of one after a city has joined the automatic monitoring program. (0-3km) is a dummy variable that equals one if cells are located within 3km of a city's monitoring stations. $PM_{2.5}^{2008-2011}$ is the average city-level $PM_{2.5}$ and citypopulation$^{2008-2011}$ is the average city population over the 2008–2011 period. Other city-level controls are the average city-level GDP from 2008 to 2011, the number of monitors in each city, the maximum distance between cells and monitors within a city, and a dummy variable that indicates whether or not a city is an environmental priority city. The Concurrent Policy refers to the city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level. Significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A8—: Validating Thermal Anomalies Data: Extensive Margins

Dependent variable:	Presence of any polluting firm		Presence of any power plant	
	(1)	(2)	(3)	(4)
Thermal Anomalies Presence	24.35***	44.26***	22.91***	37.70***
	(0.1384)	(0.000)	(0.1408)	(0.000)
Marginal Effect	*0.997****	*0.996****	*0.995****	*0.992****
	(0.000)	*(0.000)*	*(0.001)*	*(0.000)*
City FE		X		X
Observations	95,168	68,161	380,672	240,188

Notes: This table shows the association between thermal anomalies and polluting firms or power plants at the extensive margin, using the logit model. In columns (1) and (2), the dependent variable is a dummy variable that equals one if there are any polluting plants within a 10km-by-10km cell. The polluting plants come from the MEE's Key Centrally Monitored Polluting Enterprises database. In columns (3) and (4), the dependent variable is a dummy indicator that equals one if there is any power plant within the 10km-by-10km cell. The power plants sample is obtained from the China Emissions Accounts for Power Plants (CEAP). "Thermal Anomalies Presence" is a dummy variable that equals one if there are any thermal-related economic activities in a cell. Columns (2) and (4) include city-fixed effects. Standard errors are clustered at the city level. Significance: *p<0.1; **p<0.05; ***p<0.01.

Table A9—: Validating Thermal Anomalies Data: Intensive Margins

	Dependent variable: $\ln(PM_{2.5})$	
Sample	Polluting firms	Power plants
	(1)	(2)
ln(FRP+1)	0.129***	0.136***
	(0.009)	(0.004)
Observations	1,806	10,491
R-squared	0.108	0.102

Notes: This table shows the relationship between the intensity of the thermal anomalies observed and the satellite-derived pollution levels of firms or power plants at the intensive margins. The samples are restricted to only those grid cells with polluting firms or power plants. The polluting plants are defined using the MEE's Key Centrally Monitored Polluting Enterprises database, and the power plants sample is obtained from the China Emissions Accounts for Power Plants (CEAP). The dependent variable is $\ln PM_{2.5}$, defined as the natural logarithm of the cell-level yearly satellite-based $PM_{2.5}$. FRP measures the intensity of thermal-related economic activities, which is defined as the average rate of radiant heat output within a 10km radius of polluting firms, which is based on the rate at which fuel is consumed, and smoke emissions are released. Standard errors are clustered at the city level. Significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A10—: Event Study: The Effect of Monitor Automation on Air Pollution within 3km of a Monitor

	Dependent variable:	
	$\ln(PM_{2.5})$	ln(AOD)
	(1)	(2)
(0-3km)×before4	0.011	-0.0007
	(0.009)	(0.0023)
(0-3km)×before3	-0.001	0.0037
	(0.012)	(0.0028)
(0-3km)×before2	-0.004	-0.0030
	(0.011)	(0.0031)
(0-3km)×after0	-0.018	-0.0006
	(0.015)	(0.0029)
(0-3km)×after1	-0.033**	-0.0048*
	(0.013)	(0.0028)
(0-3km)×after2	-0.020	-0.0081***
	(0.017)	(0.0031)
(0-3km)×after3	-0.036**	-0.0163***
	(0.014)	(0.0031)
CellFE	X	X
YearFE	X	X
Year FE × $\text{citypopulation}^{2008-2011}$	X	X
Year FE × $PM_{2.5}^{2008-2011}$	X	X
Year FE × Other City-level Controls	X	X
Concurrent Policy	X	X
Observations	10,413,717	10,407,855
R-squared	0.975	0.964

Notes: The table reports the event study results of monitor automation on air pollution with different dependent variables. Column (1) shows the effect of monitor automation on $\ln(PM_{2.5})$ of monitored areas (within 3km of a monitor; Figure 3, and column (2) shows the effect of monitor automation on the annual ln(AOD)in monitored areas (within 3km of a monitor; Figure A4). All regressions control for cell-fixed effects, year-fixed effects, and time dummy interactions. $PM_{2.5}^{2008-2011}$ is average city-level $PM_{2.5}$ and $\text{citypopulation}^{2008-2011}$ is the average city population over the 2008–2011 period. Other city-level controls are the average city-level GDP from 2008 to 2011, the number of monitors in each city, the maximum distance between cells and monitors within a city, and a dummy variable that indicates whether or not a city is an environmental priority city. The Concurrent Policy refers to the city-level concurrent PM_{10} and $PM_{2.5}$ reduction targets. Standard errors are clustered at the city level. Significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A11—: Placebo Effects of Pseudo Automation Treatment on Cities without Monitors

	Dependent variable: $\ln(PM_{2.5})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Monitor Area:	Environment Bureau	Government Offices	All	Environment Bureau	Government Offices	All
Automation Wave:		2			3	
(0-3km)×Auto	-0.070	-0.022	-0.059	-0.063	-0.016	-0.054
	(0.052)	(0.021)	(0.033)	(0.053)	(0.014)	(0.034)
CellFE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Year FE × $\text{citypopulation}^{2008-2011}$	X	X	X	X	X	X
Year FE × $PM_{2.5}^{2008-2011}$	X	X	X	X	X	X
Observations	163,746	163,746	163,746	163,746	163,746	163,746
R^2	0.980	0.980	0.980	0.980	0.980	0.980

Notes: This table presents the placebo effects of monitor automation on cities that had never received the monitoring automation treatment. $\ln PM_{2.5}$ is the natural logarithm of the cell-level yearly satellite-based $PM_{2.5}$. To make them a comparable control group to our treatment group, we identify "placebo" monitor spots in these nine cities. By checking the existing monitor siting rules, we assigned the counterfactual monitor/s to the location of 1) the municipal Environmental Protection Bureau, 2) the municipal government building, or 3) both. Further, we assigned their fake automation timing to be either in Wave 2 or 3, denoted by Auto. (0-3km) is a dummy variable that equals one if the cells are located within a 3km radius of a city's "pseudo" monitoring stations. In Column (1) and Column (4), monitors are sited in the environment bureau buildings, while in Column (2) and Column (5), they are sited in government office buildings. In Columns (3) and (6), monitors are assigned to both environment bureau and government office buildings. $PM_{2.5}^{2008-2011}$ is average city-level $PM_{2.5}$ during the 2008–2011 period and $\text{citypopulation}^{2008-2011}$ is the average city population from 2008 to 2011. Standard errors are clustered at the city level. Significance: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table A12—: Summary of Government Documents Mentioning Strategic Cleaning

Type	Policy Measures	Number of Government Documents
Coal and other energy pollution control	Clean energy replacement	2
	Boiler renovation	16
Transportation pollution control	Yellow-label vehicles (high-emission vehicles)	2
	Travel restrictions	2
Dust pollution control	Spraying Water	16
	Windproof and dust suppression nets	6
	Wet cleaning	2
	Dust suppression/suction vehicles	3
Agricultural and other pollution control	Banning open burning	4
	Banning outdoor cookings	22
Industrial pollution control	Shutdown	3
	key monitoring enterprises	2

Notes: This table reports measures for strategic cleaning which mention in the government documents and the number of documents for each kind of strategic cleaning measures. There are 121 government documents that mention strategic cleaning in total.

Table A13—: Mechanism: Effect of Automation on Local Relative Humidity (Monthly)

Dependent Variable:	ln(Humidity)				
	(1)	(2)	(3)	(4)	(5)
Unmonitored Areas:	All	All	All	Winter	Summer
Variables					
Auto	-0.0053	-0.0054	0.0025	-0.0057	0.0064
	(0.0065)	(0.0065)	(0.0077)	(0.0100)	(0.0084)
(0-3km)×Auto		0.0288***	0.0210**	0.0335***	0.0094
		(0.0082)	(0.0083)	(0.0084)	(0.0077)
Cell	X	X	X	X	X
Yearmonth	X	X	X	X	X
Climate Controls			X	X	X
Fit statistics					
R^2	0.92948	0.92948	0.95959	0.96254	0.95638
Observations	11,222,880	11,222,880	11,222,880	4,676,200	6,546,680

Notes: This table presents the effects of the monitor automation program on satellite-based relative humidity (monthly) with meteorological data from He et al. (2020). The variable "Auto" is a treatment indicator that equals one after a city has joined the automatic monitoring program, while the dummy variable "(0-3km)" equals one if the cells are located within a 3km radius of a city's monitoring stations. The climate controls include temperature, precipitation, and wind. Columns (1) to (3) reports the results for the whole sample period. Column (4) reports the results for the winter period from October of one year to February of the next year, while Column (5) reports the estimation results for the summer period from March to September of a year. Standard errors are clustered at the city level, and significance levels are indicated by asterisks: *p<0.1; **p<0.05; ***p<0.01.

Table A14—: Mortality and Morbidity Impacts of Uneven Pollution Control

Distance from Monitors	Population ($\times 10^3$ *person*)	Excess Death Reduction ($\times 10^3$ *person*)	Total Monetary Value of Excess Death Reduction (*billion \$*)	Total Healthcare Spending Savings from $PM_{2.5}$*Reduction* (*billion \$*)	Per capita Monetary Value of Excess Death Reduction (*\$*)	Per capita Healthcare Spending Savings from $PM_{2.5}$*Reduction* (*\$*)
	(1)	(2)	(3)	(4)	(5)	(6)
(0-3km)	118970.12	13.06	15.02	0.25	126.22	2.10
(3-6km)	92787.05	9.22	10.6	0.18	114.24	1.90
(6-9km)	47720.46	4.29	4.93	0.08	103.41	1.72
(9-15km)	72816.85	5.94	6.83	0.11	93.85	1.56
(15-21km)	63986.63	4.81	5.53	0.09	86.41	1.44
(21-30km)	87327.55	6.05	6.95	0.12	79.63	1.33
(30-45km)	127270.47	7.29	8.39	0.14	65.88	1.10
(45-60km)	107054.99	5.29	6.08	0.1	56.84	0.95
(60-90km)	128741.45	4.15	4.77	0.08	37.09	0.62
(90-120km)	54978.79	0.51	0.59	0.01	10.67	0.18
(120-150km)	21358.18	-0.34	-0.4	-0.01	-18.52	-0.31
(¿150km)	22651.89	-1.54	-1.77	-0.03	-78.36	-1.30
Total	945664.44	58.72	67.53	1.12	677.37	11.28

Notes: This table presents various distance bins from the monitors, the monetized health benefits of automation— the value of $PM_{2.5}$-attributable death reduction and healthcare spending saved annually. Column (1) shows the corresponding population of each distance bin. Columns (2)–(6) report the benefits, as shown in the heading. These outcomes are computed using the pollution reduction from automation, which is denoted by $\Delta PM_{2.5}^{welfare} = \alpha \times Auto \times PM_{2.5}^{pre} + \sum_{n=(0-3)}^{(>150)} \beta_n Auto_{ct} \times Bin_n \times PM2.5_{2.5}^{pre}$. $PM_{2.5}^{pre}$ is the average cell-level yearly satellite-based $PM_{2.5}$ from 2008 to 2011 (the pre-treatment period). *Auto* is the treatment indicator that equals one after a city has joined the automatic monitoring program. The annual reduction of excess deaths in column (2) is equal to the $PM_{2.5}$-attributable monthly mortality rate 3.25% from He, Liu and Zhou (2020) (i.e., a 10 $\mu g/m^3$ increase in $PM_{2.5}$ increases monthly mortality by 3.25%) $\times$ pollution reduction calculated above ($\Delta PM_{2.5}$)/10 $\times$ population$_{2015}$ $\times$ 12 months. Based on Fan, He and Zhou (2020), the average value of a typical Chinese person's statistical life was around 1.15 million USD in 2015. Column (3) then infers the monetary value of lives saved from $PM_{2.5}$ reduction. According to Barwick et al. (2018), a medium-run reduction of 10 $\mu g/m^3$ in daily $PM_{2.5}$ would lead to \$22.4 annual savings in healthcare spending per household. Given that the average household size is 3 people (source: National Bureau of Statistics, UNICEF China, UNFPA China, 'Population Status of Children in China in 2015: Facts and Figures', 2017) and using population data in 2015, the healthcare spending savings are thus calculated as population$_{2015}$/3 $\times$ $\Delta PM_{2.5}/10\times$ \$22.4 in Column (4). Columns (5) and (6) report the per capita health benefits from reduced mortality and morbidity.

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