Co-opting Automation: How Technology Reorganizes Political Discretion in China*

Guoer Liu†

Abstract

States increasingly govern through machines rather than humans. These automated systems are typically seen as technical upgrades that improve accuracy, efficiency, and transparency by constraining political discretion. I argue instead that automation reorganizes discretion, constraining it in rule application while reallocating it upstream to system design, where choices are harder to observe and easier to justify on technical grounds. Analyzing China's automated ambient air quality monitoring network (2012–2020) with original georeferenced datasets on monitoring stations, pollution sources, hourly readings, and satellite imagery, I find systematic evidence of strategic design: polluted areas have 8.7% fewer stations than expected, stations are 11% more likely to be placed in greener locations, and monitors experience 2% more downtime during pollution spikes. These patterns thus suggest the rich and often overlooked interplay between technology and political institutions behind automated governance.

*Pre-edited version. Forthcoming in *World Politics*, 79, no. 3 (July 2027).

†Assistant Professor, Department of Political Science, University of California, San Diego. Email: guoerliu@ucsd.edu.

Governments worldwide are embracing automated systems to perform many core functions, from environmental monitoring to traffic enforcement, tax audits, and welfare allocation. These systems are often promoted as technical solutions to perennial problems of capacity and incentives in governance. They improve states' ability to collect and analyze information, enforce regulations, and limit opportunities for human intermediaries to exercise discretion.[1] The promise is appealing. When officials manipulate government statistics, shirk their responsibilities, or enforce rules selectively,[2] automation is expected to limit these forms of discretionary behavior through standardized protocols and mechanical procedures.[3]

The expectation that automation constrains political discretion, however, conflates two distinct sites of discretion: discretion in rule *application* and discretion in rule *design*. I argue that automation constrains discretion in application (how individual cases are handled) but reallocates discretion to design (how the system is configured in the first place). Decisions once made publicly, case by case, are now carried out by standardized and impersonal procedures. Yet discretion does not disappear: automation moves it upstream, into choices that are harder to observe, easier to justify on technical grounds, and made before any information is produced.

A critical but often overlooked site of this upstream discretion is physical infrastructure. Networks of sensors, monitors, and cameras form the backbone of many automated systems.[4] Once deployed, this infrastructure is difficult to move or reconfigure. Its spatial fixity brings clear technical advantages, enabling consistent data collection that reduces human error, shirking, and manipulation.[5] But fixity also creates strategic tensions. Political priorities shift, yet the infrastructure does not. Underlying conditions evolve, yet the system records them in the same way. Design choices determine which indicators are monitored for governance purposes, how they are measured, and which variations are amplified or muted. Once infrastructures are deployed, many of these choices are largely locked in. Designing that

[1] E.g., Jerven (2013); Wallace (2016); Herrera and Kapur (2007).

[2] E.g., Martinez (2022); Wallace (2022); Aragão and Linsi (2022); Cook and Fortunato (2023); Knox, Lowe and Mummolo (2020); Eckhouse (2021).

[3] E.g., He, Wang and Zhang (2020); Greenstone et al. (2022); Xu (2021); Beraja et al. (2023).

[4] In the environmental science literature, monitoring siting is a well-researched area (e.g., Piersanti et al. 2015; Duyzer et al. 2015; Baca-López et al. 2021).

[5] Greenstone et al. (2022); Brombal (2017); Fowlie, Rubin and Walker (2019).

infrastructure therefore becomes a strategic, forward-looking exercise. Officials must anticipate how political priorities may shift and how conditions on the ground may evolve, and decide in advance how the system should respond. How do political incentives and evolving conditions jointly shape the design and management of automated systems?

This paper answers this question through the empirical case of China's automated ambient air quality monitoring network between 2012 and 2020. The Chinese national government launched this initiative in response to a dual crisis: air pollution severe enough to cause an estimated 1.6 million deaths per year[6] and a bureaucracy in which environmental data were routinely manipulated.[7] Thousands of fully automated stations were deployed nationwide to collect and process real-time data on pollutants. These data are publicly released and have been used to support public health warnings and trigger emergency government responses.[8] The initiative aimed to standardize measurement, eliminate local manipulation, and restore public trust. Existing research shows that automation has indeed improved data quality relative to manual reporting.[9] But recent studies also find that automated stations consistently report lower pollution levels than alternative benchmarks.[10] The combination of improved data integrity and systematically lower readings motivates the empirical analysis of how political discretion is reorganized after automation.

I focus on three complementary dimensions of the monitoring infrastructure across space and over time: the number of monitoring stations, their geographic placement, and their operational patterns. For this purpose, I constructed four original time-series cross-sectional datasets: (1) a georeferenced dataset of air quality monitoring stations (2008-2022); (2) hourly readings from all automatic stations (2014-2022); (3) the complete georeferenced registry of pollution permits in China (2020-2022); and (4) satellite-derived vegetation density indicators at 30-meter resolution covering China's entire land surface (2008-2016).

Using descriptive, correlational, and causal inference methods, I find three systematic patterns in

[6] Rohde and Muller (2015).

[7] E.g., He, Wang and Zhang (2020); Ghanem and Zhang (2014); Kostka (2016); Wallace (2022).

[8] Greenstone et al. (2021).

[9] Greenstone et al. (2022).

[10] E.g., Turiel and Kaufmann (2021); Tang, Wang and Yi (2022); Shen (2022).

how monitoring infrastructure is designed and managed. First, automatic monitors are underdeployed by 8.7% in more polluted prefectures, relative to national guidelines. Second, greener sites were 11.0 percentage points more likely to be chosen for new automatic stations, compared to locations with pre-existing manual stations. Third, exploiting a severe pollution event with a synthetic difference-in-differences design, I find that affected prefectures experience 2.0% more system downtime during pollution spikes compared with unaffected locales during the same period. While no single finding is conclusive on its own, the range of outcomes allows me to evaluate competing explanations, including capacity constraints, administrative efficiency, and popular demand. None can account for all three patterns.[11] Strategic design offers the most consistent explanation.

This paper makes two contributions. First, it develops a theory of how automation reorganizes political discretion. The conventional view suggests that automation constrains official discretion and thereby reduces manipulation.[12] I show that the relationship is more nuanced: when political incentives persist and direct manipulation becomes difficult under automation, discretion shifts upstream into the design choices that govern what kind of information is produced in the first place.

Although China is the empirical focus, this theory travels beyond it. When states turn to automation, design choices invite strategic choices, and the technical nature of these systems can shield those choices from scrutiny. But this process does not unfold uniformly. It depends on scope conditions, among which political institutions and capacity are particularly important. Institutions determine how much friction surrounds system adoption and design. Where the rule of law, separation of powers, norms, public debate, and media scrutiny impose constraints, discretion in design is harder to exercise quietly.[13] New York City spent twelve years (2001-2013) seeking state legislative approval to install automatic speed cameras, repeatedly blocked in the transportation committee, and when approval finally came, it required reauthorization every five years. By contrast, China rolled out a nationwide monitoring system in less than four. Where institutional checks and balances are low, automation reorganizes discretion with little scrutiny. Where they are robust, design itself becomes politically contested. State capacity matters as

[11] Spirling and Stewart (2022).

[12] E.g., Greenstone et al. (2022); He, Wang and Zhang (2020); Lin and Qian (2024).

[13] Greitens (2020).

well. Adopting automated systems at scale requires upfront investment, administrative coordination, and sustained system maintenance. China can afford these costs. Not all governments can. Where capacity is limited, the scope for strategic design is limited as well.

Second, this paper contributes to the empirical literature on information politics, especially in authoritarian states.[14] I shift attention from *ex post* distortion to *ex ante* design, a contrast that sharpens as states turn to sophisticated technology to govern. Existing research focuses on distortion after information is produced, emphasizing regulatory gatekeeping,[15] direct technological interference with information flows,[16] and, in environmental politics, downstream manipulation by regulators and firms.[17] I identify system configuration as another strategic site of information statecraft. Rather than manipulating outputs after the fact, authorities shape information before any data is produced by deciding what data are collected, where they are collected, and how the system operates. Specifically, the empirical analysis foregrounds the physical infrastructure that underpins automated systems, an aspect that has received little systematic analysis. While technology can produce truthful information, decisions about what constitutes the *whole* truth—what gets measured, when, and how—remain inherently political choices that define the boundaries of transparency.[18]

1 Automation and Political Discretion

1.1 The Appeal of Automation

Automated governance systems are information infrastructures designed to collect and process information for governing purposes, according to predefined rules and procedures. They generate standardized signals that inform—or directly trigger—regulatory action, such as public warnings, penalties, or inspections, or benefit determinations. Consider ambient air-quality monitoring in China, the central case of this paper. Automated monitors sample air, analyze pollutant concentration,s produce

[14] Wallace (2016).

[15] E.g., Berliner (2014); Honig, Lall and Parks (2023); Beraja et al. (2023); Xu (2021).

[16] E.g., King, Pan and Roberts (2013); Roberts (2018); Lutscher (2023); Hellmeier (2016); Treisman and Guriev (2023).

[17] E.g., Monogan III, Konisky and Woods (2017); Grainger, Schreiber and Chang (2019); Karplus, Zhang and Almond (2018); Karplus and Wu (2023); Mu, Rubin and Zou (2024).

[18] E.g., Scott (1998); Lee and Zhang (2016); Brambor et al. (2020).

and publish reports, trigger regulatory interventions when pollution thresholds are exceeded, and provide the basis for evaluating environmental governance. Similar architecture appears in other domains, too. Speed cameras monitor traffic, capture license plates of speeding vehicles, and automatically issue civil citations with fines. Tax audit systems process financial records, generate standardized risk scores, and flag cases for inspection. Welfare eligibility algorithms classify applicants based on individual data, determining who receives benefits and who does not.

The appeal of automation is easy to see. Automation can expand state capacity. Machines do not get tired, anxious, ambitious, or afraid. They perform the same task in the same way, again and again, according to predetermined rules. The mechanical consistency not only reduces human errors in performing tasks, but also makes machines reliable in ways that human labor cannot match. With stable electricity and computing power, automated information systems can collect data continually, process it instantly, and keep going without rest. They generate streams of *in situ* information that move with the pace of real-world conditions rather than the clock of bureaucratic reporting. Because automated systems scale easily, they appear especially well suited for governing large, complex problems by providing broader coverage, more frequent updates, and finer-grained detail.

Automation also promises to address incentive problems by constraining discretionary power—the ability to choose among multiple permissible actions when rules do not fully determine behavior.[19] Discretion leaves room for selective enforcement, strategic calculation, or personal bias. Machines do not negotiate targets, look away from problems, or soften unpleasant information before passing it upward or making it public. As sensors, instruments, and software improve, it is tempting to imagine a world where politics recedes as technology advances, one in which governance is always neutral and impersonal at the moment of decision. Automated systems, therefore, are valued for making governance appear faster, clearer, and more objective.

1.2 Two Sites of Political Discretion: Application and Design

Political discretion operates at two sites: the application of rules to individual cases and circumstances, and the design of the rules themselves. Automation can narrow discretion in rule application. This is no

[19] Lipsky (2010).

trivial achievement. Often, rules are fixed on paper but flexible in practice: applied unevenly, adjusted informally, or selectively enforced as conditions change. It is precisely this gap between formal rules and actual implementation that gives automation its appeal. When pollution reflects poorly on governments, officials are tempted to underreport it; when pollution is used to justify additional public funds, officials are likely to overreport it. Traffic officers may, even unconsciously, stop drivers from certain ethnic backgrounds more often than others. Tax audits can get delayed when agencies face funding cuts. Welfare caseworkers interpret eligibility criteria more generously for some applicants than others. In each case, discretion is exercised—and sometimes abused—by human agents. Automated systems are built to operate mechanically. When they function consistently, automation commits the state to applying rules repeatedly and impersonally, even when doing so becomes politically inconvenient.

But application is only one site where discretion operates. Automation reallocates it to another: system design. Automated systems do record reality, but they only record a particular version of reality—one filtered through physical infrastructure, measurement algorithms, and formal regulations. These elements define, *ex ante*, the operative rules of the system: what gets observed, how it is measured, what counts as compliance or violation, when action is triggered, and who is held accountable. These are design choices. They determine the parameters of the system itself, not how individual cases are enforced within it. When automation constrains discretion in application, it also increases the political stakes of system design. The strategic question shifts from how rules are applied in individual cases to how the system is configured. Automation does not depoliticize governance; it moves the politics upstream.

1.3 Reorganized Discretion and Information Consequences

If automation reorganizes discretion rather than eliminates it, what is the value added of automation? Reorganized discretion changes the character of the information the system produces. The information consequences shed light on an equilibrium logic: automation produces information that, while not necessarily accurate, is legible over time, giving key actors reasons to sustain the system rather than reverse it. I explain these information consequences first; how discretion is reorganized depends on specific institutional contexts, which I take up in the next section.

Automation changes information production in two ways. First, by regularizing discretion downstream, it reduces noise in information. In manual systems, information varies across agents, equipment, timing, and incentives. Automation compresses these sources of variation. The resulting data may still be inaccurate, but they are produced through standardized protocols and evaluated against fixed criteria in consistent ways.

Second, by reallocating discretion upstream, automation shapes the bias embedded in the system. The systematic gap that remains between the collected information and the underlying true condition, or bias, depends on the discretion exercised in system design. Automated systems operate only within the parameters built into them. Choices about infrastructure configuration, measurement standards, reporting thresholds, and calibration determine how closely the system tracks underlying conditions. To the extent that political actors fine-tune these operative rules strategically, bias will be embedded in the architecture itself.

Automation, therefore, does not eliminate bias; it stabilizes it. Information may still deviate from the truth, but it deviates in regularized ways. The relationship between underlying conditions and collected information becomes stable. When that mapping is stable, actors can learn from repeated exposure, update their expectations, and infer trends over time. Even when levels are biased, the signal is interpretable.

A simple metaphor illustrates the intuition. Suppose you want to know your weight but do not have a scale. You ask other people instead. The answers vary: a close friend gives one number; a fitness coach gives another. Each observer sees you differently and faces different incentives, so the signal drifts with the source. Now imagine instead that you have a faulty scale. It tells you that you weigh 60 pounds. The reading is wrong—it obviously underreports your true weight by some unknown amount—but it does so consistently. Step on it several times and you see the same number; as your diet and exercise change, the reading changes steadily in the expected direction. You still do not know the true level. But you do learn whether your weight is rising or falling relative to a fixed baseline. The baseline is biased, but the signal is still informative.

Bias need not disappear for a signal to be meaningful; but it must be stable. A consistently biased instrument is still more informative than the alternatives: having no instrument at all, or having one that fluctuates with who is using it and the circumstances. By regularizing discretion downstream and reallocating it to design, automation converts unstable variation into structured bias. The resulting information may be inaccurate, but it becomes legible. Change over time can be tracked, comparisons can be made, and trends can be inferred even when the absolute level is systematically off.[20]

How much discretion remains upstream depends on the specific institutional context in which system design occurs: the technical domain, the actors involved, and the incentives they face. The next section develops this logic through China's ambient air quality monitoring system.

2 Strategic Environment: Automating Air Quality Monitoring in China

Air pollution in China is estimated to cause more than a million premature deaths each year.[21] For years, however, the true scale of the crisis was obscured by bureaucratic manipulation and weak monitoring capacity.[22] The political stakes of environmental information became visible during the 2008 Beijing Olympics, when international scrutiny drew public attention to the large discrepancy between official statistics and independent readings, most notably from the U.S. Embassy's rooftop air quality monitor, which automatically collected and broadcast data via Twitter.[23] The discrepancy not only embarrassed the Beijing municipal government; it undermined the credibility of official information and fueled public dissatisfaction.[24]

Amid growing concerns over environmental degradation and declining credibility, the Chinese central government launched a nationwide automation initiative in 2012 that reshaped environmental monitoring. The initiative introduced three major changes. First, automated and standardized monitoring technologies replaced manual data collection and reporting, which made direct manipulation

[20] Liu (2026) develops a theoretical model and provides supporting experimental evidence.
[21] Rohde and Muller (2015).
[22] Ghanem, Shen and Zhang (2020); Brombal (2017).
[23] Kintisch (2018); Barwick et al. (2024).
[24] Steinhardt and Wu (2016); Alkon and Wang (2018).

much more difficult.[25] Second, monitoring coverage expanded from 113 key prefectures to a centralized network of approximately 1,800 automatic stations covering all prefectures by 2020.[26] Third, the system shifted from sporadic reporting to hourly updates accessible through multiple public-facing platforms. Real-time air quality data became accessible through smartphones and widely used mobile applications, significantly increasing transparency in environmental information (see Supplementary Information (SI) Section A.1 for more information). These data also feed directly into early pollution warning systems, triggering contingency plans when air quality deteriorates.[27]

Automation does not alter the underlying institutional arrangements for environmental monitoring, however. Project implementation remains delegated to local governments. Information asymmetries persist between the national authority (the principal) and local governments (the agents). Their interests can be misaligned: the principal relies on reported numbers—even when produced automatically—to exercise bureaucratic control, while local officials rely on those same numbers to meet performance targets. These are precisely the conditions under which data manipulation arise (see SI Section A.2).

What automation does change is where discretion can be exercised. When automation reduces officials' ability to directly manipulate data and institutional incentives remain, discretion shifts to implementation decisions. In the case of air quality monitoring, local governments exercise agenda control over infrastructure deployment: they propose whether to add automatic stations, where to place them, and how to operate them. Even when these decisions require formal approval from the national authority, local governments set the menu from which higher levels choose. The strategic question shifts from whether to alter reported information to how to shape the conditions under which information is generated.

[25] Greenstone et al. (2022).
[26] See *Xinhua News Agency*'s report here.
[27] Zhao et al. (2018); Zhang et al. (2024).

2.1 Exercising Discretion through Design

2.1.1 Fixed Infrastructure and Policy Uncertainty: Political conditions

Automated monitoring depends on physical infrastructure that, once installed, is largely fixed. Political priorities, by contrast, often change. This asymmetry creates a strategic tension: local governments responsible for implementation face incentives to design systems that *hedge* against shifting political priorities.

In air quality monitoring, the relevant infrastructure is the automatic stations. The scale of infrastructure investment made these choices consequential. A single automated station costs approximately 1.5 million RMB (approximately $210,000) in 2017, and 60% of its components and devices need replacement within five years. The total infrastructure investment was estimated at 5.2 billion RMB between 2013 and 2020.[28] Regulatory rules also prohibit relocation without special administrative approval, and official guidelines require that the surrounding area remain stable with no construction for a considerable period. [29] Because stations cannot be easily moved or adapted as circumstances evolve, implementation decisions must be made with long time horizons in mind.[30] Officials had to anticipate future constraints and build contingencies into system design from the start.

These constraints are compounded by a volatile policy climate. Beijing's push for automated monitoring, together with stricter air pollution performance metrics, elevated environmental protection to a national priority. But this shift did not immediately translate into stable expectations for local governments, who had long been evaluated primarily on economic performance.[31] The center at times escalated enforcement through "blunt force" measures—such as ordering uniform shutdowns

[28] Automated monitoring also demands ongoing investment in specialized expertise. System operators, maintenance technicians, and security personnel are essential, with annual maintenance costs reaching 150,000 RMB ($21,000) per station. All estimates are from Guangfa Security's industrial sector report (2017).

[29] State Environmental Protection Administration (2007); Ministry of Environmental Protection (2013).

[30] Fixed locations also pose other administrative hurdles. For instance, site selection guidelines require assessing "the feasibility of obtaining land use permits and select sites where such permission is assured from among all available options" (China National Environmental Monitoring Centre 2014). Even when sites satisfy technical criteria, practical considerations can make them impractical. As Zuzhao Huang, Director of the Guangzhou EMC Technical Center, notes, "Reliable water and electricity supplies pose potential challenges [for site selection]. Given that monitoring operations need to run continuously, 24/7, any power interruptions could disrupt data collection and affect the overall dataset" (See *Southern Daily*'s report).

[31] Ding (2022).

of polluting factories—despite the substantial costs to local economies and employment.[32] Direct interventions certainly signaled seriousness, but reliance on administrative orders did little to stabilize expectations about how environmental priorities would be enforced over time. Local officials faced risks on both sides: pursuing rapid growth could invite sudden environmental crackdowns; while complying with pollution control depressed output, revenue, and employment—the very metrics that continued to structure performance evaluations. The core problem was not simply conflicting goals, but uncertainty about which priority would prevail, and for how long.

When infrastructure is fixed and policy is volatile, officials hedge in how they implement policy. The risks local governments faced were *not* symmetric. Poor readings brought concrete and immediate consequences: intrusive enforcement, political blame, and financial loss. The benefits of faithful implementation, by contrast, were diffuse and uncertain, as I show in the empirical tests below. When punishment for bad outcomes is more likely than reward for compliance, the safer political response is to reduce the likelihood that damaging data appear or travel upward unfiltered.[33] This calculus is neither unique to environmental governance nor new. As Alex Wang observes from years working with local officials, the "willingness to hide information perceived as likely to cause public dissatisfaction (or 'instability') ... is widespread."[34] The aversion also cascades through the bureaucratic hierarchy. As one environmental official recounted, when senior leaders face performance review, provincial officials pressure mid-level ministry staff by invoking political stakes and signaling that the reported numbers need to be *managed*.[35] Pressure to control damaging information can align officials across levels around a common goal: reducing the visibility of unfavorable conditions. Under automation, that effort begins with the infrastructure designed to measure them.

2.1.2 Monitoring a Moving Target: Technical Conditions

Strategic configuration during implementation is feasible because pollutant concentrations are a moving target: they vary across space and time, but not uniformly. Some pollutants, like SO_2, are concentrated

[32] Van der Kamp (2023).
[33] E.g., Kostka (2016); Cao, Kostka and Xu (2019).
[34] Wang (2013, p.428).
[35] Wang (2013, p.437).

at identifiable point sources and industrial facilities, producing sharp local gradients in ambient concentrations.[36] Measured SO_2 levels are therefore sensitive to where monitors are placed relative to emission sources. Others, like $PM_{2.5}$—a mixture of many small particles with an aerodynamic diameter of 2.5 microns or less–—reflect a combination of local emissions, secondary formation, and regional transport, producing relatively smooth spatial gradients within cities.[37] Measured $PM_{2.5}$ levels tend to be less sensitive to the precise placement of individual monitoring stations, and nearby sites often record similar concentrations over the same period. Siting decisions are therefore less consequential.

China's Air Quality Index (AQI) amplifies this unevenness. The AQI is constructed from pollutant-specific sub-indices.[38] The reported AQI at a given station and time is determined by the *maximum* across all pollutants. That is, it reflects whichever pollutant performs worst.[39] This means that spatially variable pollutants disproportionately drive reported air quality. For these pollutants, decisions about where monitoring occurs can meaningfully shape what is observed. Monitoring design therefore has the most leverage over spatially variable pollutants, and the strategic response is to site stations away from locations where those pollutants are likely to peak.

2.2 Strategic Siting in Practice

The prospect of unfavorable information created incentives to evaluate infrastructure configuration from the very beginning. A revealing example comes from Jiangsu province, where *before* the launch of the national monitoring grid in 2012, the Department of Environmental Protection conducted simulation studies of their existing network under new standards. The simulations predicted that the province's percentage of "good" air quality days would drop from 90.4% to 61.6% under the new air quality standards, falling below the new evaluation criteria.

Local authorities also invested heavily in evaluating candidate sites before fixing permanent locations. In Guangzhou (Guangdong province), for example, environmental authorities are reported to have conducted sampling across more than one hundred candidate locations before fixing the final set of

[36] E.g., See the EPA's Sulfur Dioxide Basics website.

[37] See Inhalable Particulate Matter and Health (PM_2.5 and $PM_1$0).

[38] The pollutants include particulate matter (PM_{10}; diameter less than 10 micrometers), fine particulate matter ($PM_{2.5}$; diameter less than 2.5 micrometers), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), and carbon monoxide (CO).

[39] Section 4 in Ministry of Environmental Protection (2012*b*).

national-control monitoring stations. Candidate sites were generated by overlaying a grid—typically at one- or two-kilometer resolution—onto the city's built-up area, with teams of technicians collecting synchronized measurements across these locations across multiple years, seasons, and pollutants.[40]

Whether the exercises reflected strategic intent or routine administrative caution is difficult to determine from the public record alone. What can be observed, however, is that new stations tend to be sited in cleaner environments. In Nanjing, the provincial capital of Jiangsu, two of three new automatic stations were placed in scenic areas far from the city center, with the third positioned on a university campus.[41] The pattern was not unique to Jiangsu. Guangzhou positioned seven out of ten monitoring stations in public schools; Changsha (Hunan province) placed three out of eight stations on university campuses and the remaining five on top of government buildings. All these locations are known for lush green spaces and their considerable distance from major pollution sources. The pattern attracted public attention and media scrutiny at the time, with commentators questioning whether such sites could adequately reflect everyday urban air quality.[42] These examples illustrate a systematic pattern of infrastructure configuration that I document in the next section.

3 Empirical Strategies

Demonstrating strategic infrastructure configuration presents two related empirical challenges. The first is counterfactual: I need to show not only what is observed, but also establish a plausible benchmark for how these systems would have been configured absent strategic considerations. The second is inferential: along any single dimension of infrastructure, deviations from such a benchmark may reflect technical necessity, logistical constraints, or administrative capacity rather than strategic design. Credible inference therefore requires examining multiple dimensions,[43] each subject to different non-strategic constraints, so that the overall pattern is harder to attribute to any one alternative explanation.

The research design addresses both challenges. I construct dimension-specific counterfactuals and

[40] See *Nanfang Daily*'s report on March 12, 2012.

[41] See *China News Service*'s report.

[42] See *Nanfang Daily*'s report and *Xiaoxiang Morning News*' report. The complaints I found were concentrated at the time when the automation initiative was first introduced. Similar concerns have been rare in recent years, likely because air quality has improved substantially since 2014, as I discuss in the Conclusion.

[43] Spirling and Stewart (2022).

examine strategic configuration across three distinct aspects of the monitoring network over space and time: station count (how many monitoring points exist), site placement (where stations are located), and operational patterns (how stations function over time). Each captures a different design margin, subject to different non-strategic constraints, allowing a more credible assessment of whether observed deviations reflect systematic, non-random patterns. Specifically, I ask: (1) whether monitoring stations are underdeployed in more polluted areas; (2) whether stations are disproportionately located in cleaner microenvironments following the automation initiative; and (3) whether system downtime increases during periods of elevated pollution.

To answer these questions, I constructed four original time-series cross-sectional datasets: (1) georeferenced air quality monitoring stations (2008-2022); (2) hourly readings from all automatic stations (2014-2022); (3) the population of georeferenced pollution permits in China (2020-2022); and (4) satellite-derived vegetation density indicators at 30-meter resolution covering China's entire land surface (2008-2016).

Each analysis evaluates observed infrastructure patterns against a corresponding counterfactual, tailored to the specific dimension under study. The following sections present each dimension in turn, discussing the counterfactual, data, empirical strategy, results, and alternative explanations.

4 Study 1: Station Coverage and Systematic Shortage

4.1 Counterfactual

Strategic configuration manifests through the geographic coverage of monitoring stations. When local governments face pressure to report favorable air quality performance while maintaining discretion over network implementation, they have incentives to build fewer stations in more polluted areas. Doing so reduces the risk of consistently reporting unfavorable readings that draw public scrutiny and political blame from above.[44]

The rollout of the automation initiative created this opportunity. The national government issued clear technical guidelines for station coverage, but delegated actual construction to local authorities.

[44] E.g., Ding (2022).

Compliance with these design specifications was *not* incorporated into cadre performance evaluations. Under the Target Responsibility System (TRS), officials were assessed on two criteria: first, the average air quality readings; and second, whether stations used automated technology. Whether they adhered to technical standards governing coverage or network design was not evaluated (see SI Section A.2). Therefore, automation and favorable readings were rewarded; deviations from the prescribed formula carried little consequence. This leads to the first empirical hypothesis:

Hypothesis 1 More polluted prefectures build fewer automatic stations.

To evaluate this hypothesis, I use the national government's own formula for how many stations each prefecture should have. The Ministry of Environmental Protection issued comprehensive guidelines (HJ 664-2013) specifying station requirements as a function of urban area and population (see SI Section B.1.2). Using this formula as a benchmark, I calculated the gap between each prefecture's expected and actual number of monitoring stations in 2020. This difference—expected minus actual stations—serves as the dependent variable: positive values indicate a station shortage relative to the regulatory benchmark, while negative values represent a surplus.

To be clear, I do not treat the guideline formula as a gold standard for optimal monitoring design. The formula itself may reflect the national authority's preferences, and local factors such as terrain, climate, or geography may justify departures from the prescribed numbers. What the measure captures is a pattern of implementation: the extent to which prefectures comply with centrally issued directives, regardless of whether those directives are technically or socially optimal.

4.2 Data

4.2.1 Identifying Monitoring Stations

I constructed a georeferenced panel dataset of air quality monitoring stations in China from 2008 to 2021. The dataset focuses on stations officially designated as urban assessment stations, whose readings constitute China's official air quality reports. For each station, I collected six variables: station ID, name, prefecture, longitude, latitude, and a reference indicator distinguishing stations used for technical quality control from those used in official assessments (see SI Section B.1.1).

4.2.2 Pollution Permits

Testing whether station shortages are correlated with pollution levels requires a measure of pollution that is independent of the air quality monitoring network itself. I use the aggregate volume of point source pollution permits at the prefecture level. Point source pollution is emissions from fixed, identifiable sources such as industrial facilities and gas stations, and it requires government permits regardless of how ambient air quality monitoring stations are deployed. Because permit issuance does not depend on station placement, this measure is not mechanically affected by monitoring coverage. This mitigates a key endogeneity concern: that areas may appear less polluted simply because they host fewer monitoring stations.

Other commonly used pollution measures are less appropriate for this purpose. Satellite instruments provide independent remote sensing observations, but many widely used gridded estimates of surface air pollution incorporate ground monitoring station data for calibration or data fusion, and therefore partially reflect the underlying monitoring network itself.[45] Private monitoring efforts by citizens and NGOs offer another alternative, but these lack national-scale coverage and are not systematically available. Using permit-based measures allows me to benchmark pollution exposure without reintroducing dependence on station deployment decisions.

I constructed this dataset by scraping all licensed point source pollution permits from the Ministry of Ecology and Environment's (MEE) permit management portal for 2020–2021 (see SI Section B.2). By the end of 2020, the system had achieved full national coverage, encompassing 3.04 million point sources.[46] Each permit contains multiple attributes, including company name, industrial sector, geocoordinates, pollutant types, and emission frequencies. Because polluting firms self-report emission data, key variables such as pollutant-specific emission levels and frequencies are almost always missing. I therefore use the aggregate count of permits at the prefecture level as a proxy for the density of pollution sources.[47]

[45] See the NASA presentation "Satellite-Based PM2.5 Datasets".

[46] National Energy Administration (2020); CCTV.NET (2021). This system is distinct from China's Continuous Emission Monitoring system, which monitors emission concentrations from designated key polluters (Buntaine et al. 2024, e.g.,).

[47] This measure is admittedly coarse: a count treats a restaurant and an aluminum smelter as equivalent. An emission-weighted measure would be preferable, but the substantial missing data makes this infeasible. Province fixed effects absorb systematic differences in industrial composition, and the convergence of findings across all three studies, each using different data and identification strategies, reduces the concern that this measurement limitation drives the results.

4.3 Empirical Strategy & Results

The most complete Ordinary Least Squares (OLS) regression model specification is as follows,

$$f(\text{Population}_i, \text{Built-up Area}_i) - \text{Actual}_i = \alpha + \beta \text{Pollution}_i + \lambda_j + \epsilon_i \quad (1)$$

where f is the formula in the official document.[48] Population$_i$ and Built-up Area$_i$ are the population and built-up area in prefecture i measured in 2020. Actual$_i$ is the number of observed stations in prefecture i as of January 1, 2021. Pollution$_i$ is the number of pollution permits in i in 2021. λ_j denotes province fixed effects.

The analysis shows systematic underdeployment in more polluted areas (Figure 1). OLS analysis shows that an increase of one standard deviation in pollution permits (about 1,000 permits) corresponds to 0.5 fewer monitoring stations—an 8.7% shortage relative to the average of 5.74 stations per prefecture. This pattern is robust across different model specifications and subgroup analyses. First, baseline models address the heterogeneous nature of cross-sectional data by incorporating heteroskedasticity-consistent standard errors and province-fixed effects. To improve estimation efficiency, I also implemented weighted least squares (WLS) regressions, which assign higher weights to observations with lower variance and lower weights to those with higher error variance. They yield similar results. Second, the results hold across subsamples: all monitoring stations, a subset excluding non-evaluated reference stations, and a subsample of non-capital prefectures. Third, additional robustness checks using raw station counts and generalized additive models (GAM) also support these conclusions (SI Table C.3).

4.4 Alternative Explanation: Capacity Constraint

A plausible alternative is that the observed pattern reflects capacity constraints rather than strategic design. Local governments often face binding resource constraints in environmental governance.[49] If so, deviations from national station requirements may simply reflect uneven fiscal or administrative capacity. This account predicts a straightforward relationship between prefecture wealth and compliance: more

[48] See SI Table B.1.
[49] Ding (2022).

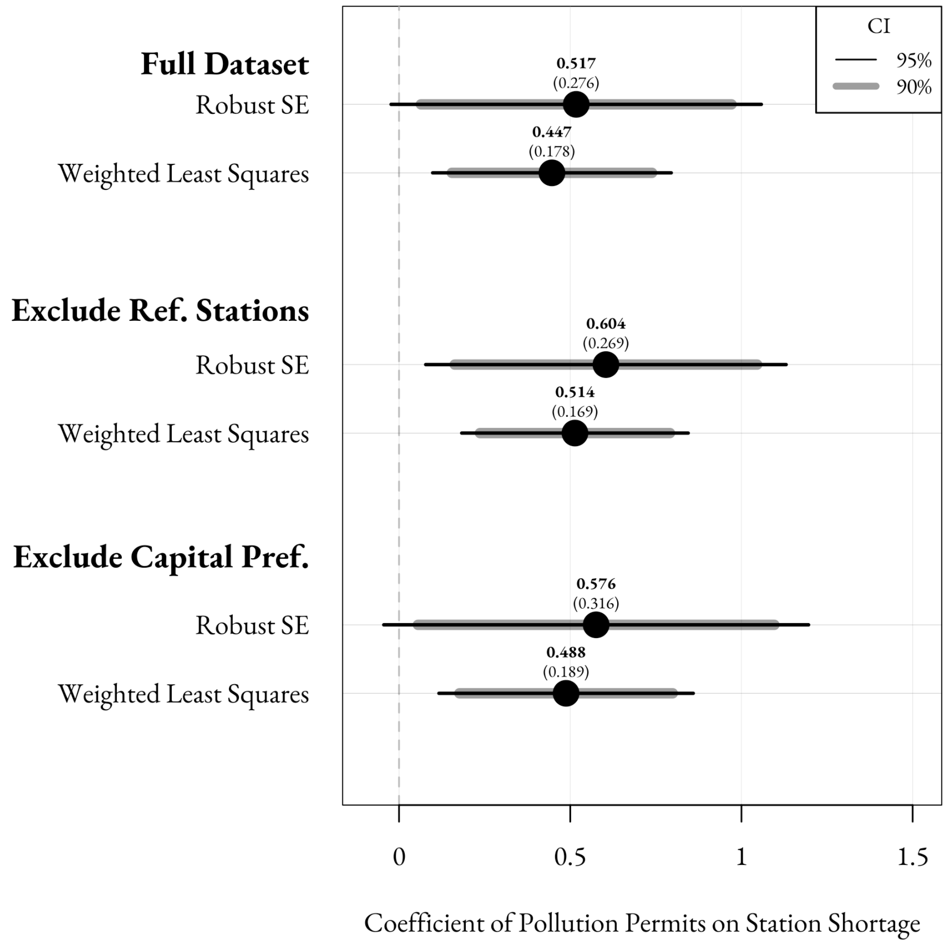


Figure 1: Correlation between pollution and station shortages in Chinese prefectures (2020). Points represent coefficient estimates from heteroskedasticity-robust models. Thin black and thick gray lines indicate 95% and 90% confidence intervals, respectively. Results show systematic station shortage in more polluted areas relative to technical guidelines.

affluent prefectures should meet national requirements, while resource-poor prefectures should fall short.

Strategic behavior suggests a more complicated empirical pattern. When local governments care more than what they are capable of building, they also weigh how additional or fewer stations should shape average pollution readings. Station deployment should then respond to both resource constraints *and* anticipated measurement consequences. Deviations from national benchmarks need not vary monotonically with resources.

The empirical pattern is more consistent with the strategic account. Figure 2 shows that 26% of prefectures fall below requirements and 25% meet them exactly, a substantial 49% actually exceed the

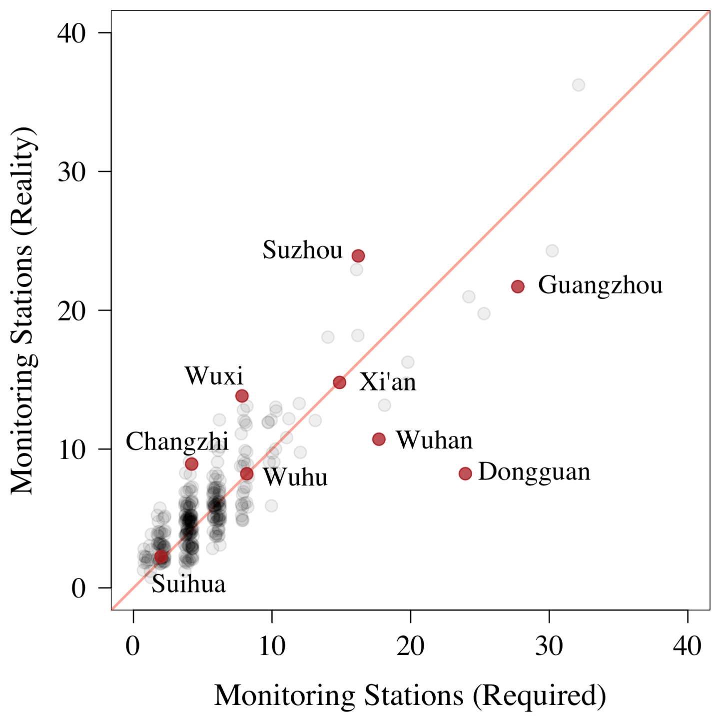


Figure 2: Comparison of actual versus required monitoring station counts across Chinese prefectures in 2020. Each point represents a prefecture, with required station counts (per technical guidelines) on the x-axis and actual implemented stations on the y-axis. Points above the 45-degree line indicate excess stations; points below indicate deficits. Selected prefectures are highlighted and labeled for illustration. Points are jittered (factor = 1.5) to reduce overlap. Distribution reveals substantial variation in adherence to technical requirements.

minimum standard. This variation does not follow a clear resource gradient. Provincial capitals like Guangzhou (Guangdong) and Wuhan (Hubei) have fewer stations than required, while less wealthy cities like Changzhi (Shanxi) exceed the minimum standards. Even prefectures with vastly different economic scales, such as Xi'an (the capital of Shaanxi) and Suihua (Heilongjiang), both adhere precisely to the guidelines. The varied implementation across economic levels suggests strategic decision-making rather than limitations due to capacity constraints alone.

The prevalence of station surpluses also points to an additional margin of strategic configuration. Building more stations can be strategic, so long as additional stations are placed in locations that effectively lower average readings across the jurisdiction. The question thus shifts from *how much* to measure to *where* to measure. I turn next to the analysis on station location.

5 Study 2: Station Siting as Deliberate Sampling

5.1 Counterfactual

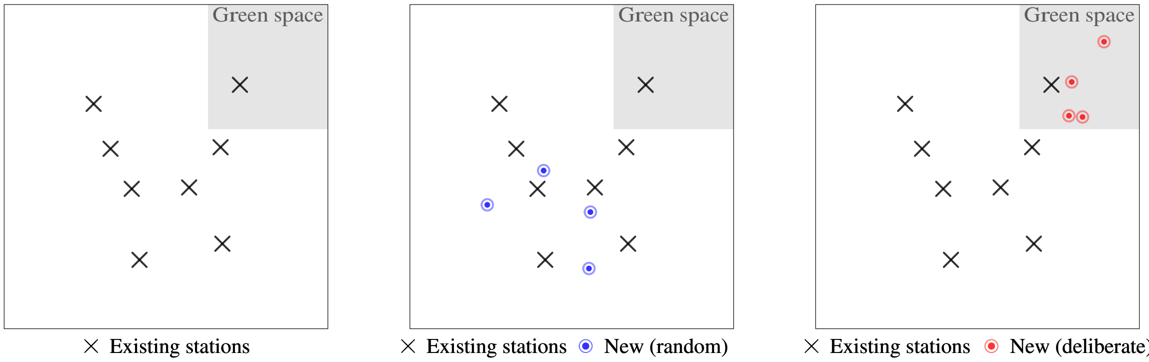
Strategic configuration also operates through the placement of monitoring stations. When local officials face pressure to improve reported air quality, they can do so—without violating formal requirements—by systematically siting automatic monitors in cleaner microenvironments, thereby lowering average readings.

The automation initiative sharpened this incentive by closing off other channels of direct manipulation. Before 2012, local officials faced relatively limited political pressure to produce favorable air quality data, and when such pressure arose, they retained discretion to manipulate readings directly.[50] After 2012, environmental indicators gained more weight in cadre evaluations, and the automation initiative also reduced discretion over data collection and reporting, making direct interference much more difficult.[51] Officials did, however, retain control over one crucial decision: where to site the automatic stations. National guidelines explicitly recognize that station placement must balance technical needs with practical considerations such as utility access, internet connectivity, and construction costs.[52] This officially sanctioned discretion preserves space for strategic influence over placement.

If officials sought to lower average readings through placement, vegetation coverage offered a natural lever. Environmental science research shows that vegetation coverage plays an important role in mitigating air pollution by cooling local temperatures, filtering airborne pollutants, and reducing nearby energy consumption.[53] Areas with greater vegetation coverage thus tend to exhibit lower pollution exposure, making them attractive sites from a strategic perspective. This leads to the second empirical hypothesis:

Hypothesis 2 Stations are sited in greener locations after automation.

[50] E.g., Wang (2013).
[51] E.g., Greenstone et al. (2022).
[52] See China National Environmental Monitoring Centre (2014).
[53] Litschke and Kuttler (2008); Janhäll (2015).



(a) Baseline (b) Random Sample (c) Deliberate Sample

Figure 3: Comparing Station Distributions with Different Sampling Strategies.

A stylized example illustrates this logic. Suppose factors influencing air quality are uniformly distributed across a prefecture. Stations placed randomly across the space would best capture the true overall air quality (see Figure 3a).[54] Now suppose the prefecture must add four new stations due to urban population growth, as required by national regulations.[55] Agencies face a choice: place the new stations randomly to maintain representative coverage as the baseline (Figure 3b), or deliberately cluster them in the prefecture's green spaces (Figure 3c). Both approaches satisfy regulatory requirements, but the second option would systematically lower reported pollution averages.

This siting logic extends beyond meeting minimum requirements. As shown in the previous section, many prefectures build more stations than mandated. When surplus stations can be placed in ways that improve average readings, expanding the network lowers average readings rather than improving sampling representativeness. Pre-automation station locations provide a valuable baseline for comparison.

5.2 Data

5.2.1 Normalized Difference Vegetation Index (NDVI)

To measure the microenvironments around station locations, I construct two panel datasets of vegetation density from NASA's Landsat 7 satellite imagery at 30-meter resolution, covering all of China from 2008

[54] The points in Figure 3a and Figure 3b are randomly generated using a pseudo-random number generator from a two-dimensional normal distribution. Points in Figure 3c are randomly sampled from the restricted area.

[55] Assume population density growth is also even across the space, to simplify the discussion.

to 2016: one at the pixel level and one aggregated to the prefecture level (see SI Section 5.2.1). Both datasets measure the Normalized Difference Vegetation Index (NDVI), which quantifies vegetation cover using the normalized difference between near-infrared and red-light reflectance. NDVI values range from -1 to 1, where higher positive values indicate denser, healthier vegetation. Values near zero typically represent bare soil or rock, while negative values indicate water bodies, snow, or other non-vegetated surfaces.[56]

Figure 4 validates this measurement approach by comparing satellite-derived NDVI values with street-view images of actual station surroundings. The figure shows two monitoring stations with distinct microenvironments in 2012: Dongsi station (white marker, NDVI = 0.10) represents a more urban environment with minimal vegetation, and Agricultural Exhibition Hall station (purple marker, NDVI = 0.34) represents an environment with considerably more greenery. The inserts display pixelated 180 $\times$ 210 meter areas surrounding each station alongside corresponding Google Earth Street View images from October 2012. The visible differences in vegetation closely track the NDVI values, confirming that satellite-derived measurements accurately capture ground-level environmental conditions around monitoring stations.

5.2.2 Empirical Strategy & Results

I test whether locations with higher vegetation coverage were more likely to be selected as new monitoring station sites. I focus on the initial network expansion (2012–2016), when all new stations were announced simultaneously in the 2012 MEP Notice.[57] This period eliminates confounding from officials learning from early implementation or adapting strategies over time.

I estimate a linear probability model with two-way fixed effects:[58]

$$\mathbf{1}\{\text{New Station Site}_i\} = \alpha + \beta \text{NDVI}_{it} + \theta_k + \eta_t + \theta_k \eta_t + \epsilon_{it} \tag{2}$$

The dependent variable is an indicator equal to 1 if pixel i was designated as the location of a newly built

[56] Burgess et al. (2012); Donaldson and Storeygard (2016).

[57] Ministry of Environmental Protection (2012*a*).

[58] A linear probability model is preferred to a logistic regression for two reasons: it avoids the multiplicative interpretation challenges of fixed effects in non-linear models and sidesteps the incidental parameter bias that can arise when estimating numerous fixed effects (e.g., Neyman and Scott 1948; Lancaster 2000.)

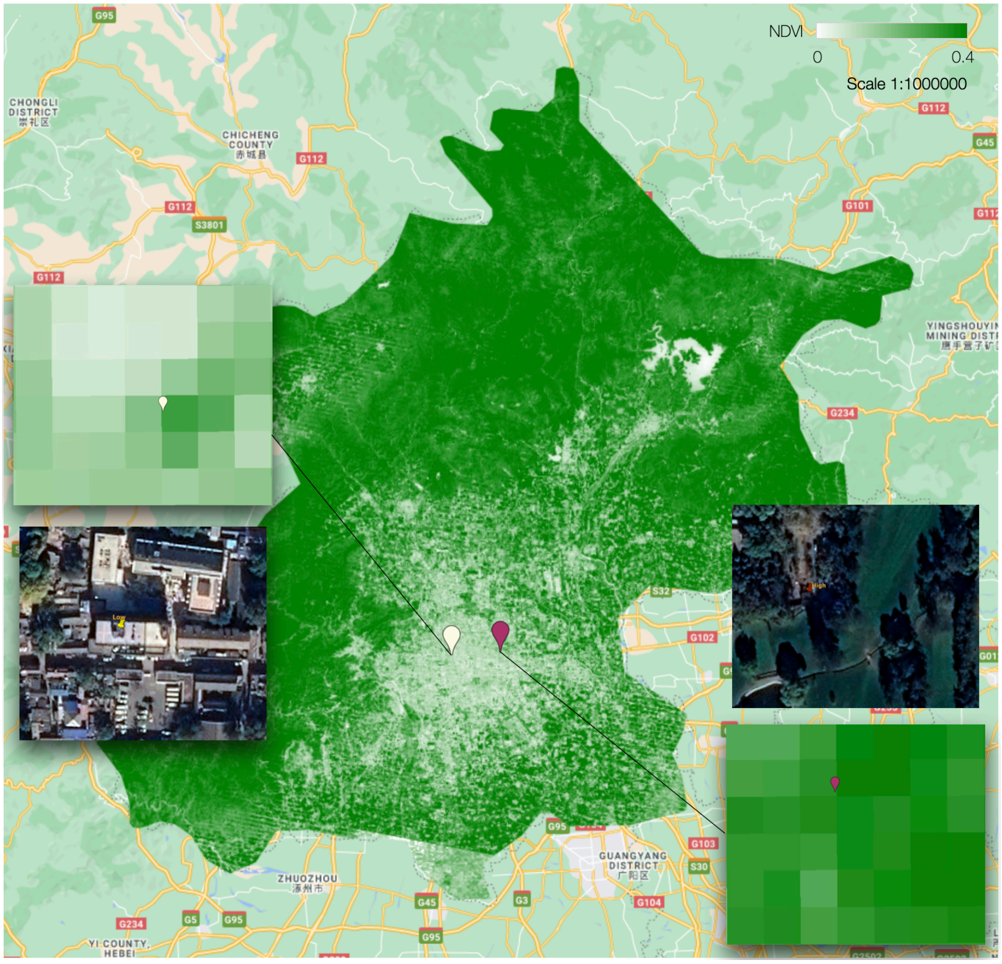


Figure 4: Vegetation coverage and monitoring station placement in Beijing. The shaded area displays the NDVI values(0 to 0.4). Two stations illustrate distinct microenvironments: Dongsi (white marker, NDVI = 0.10) and Agricultural Exhibition Hall (purple marker, NDVI = 0.34). Insets show pixelated 180 × 210 m areas and corresponding Google Earth Street View images (October 2012).

station under the post-2012 automation initiative, and 0 otherwise. The comparison group consists of pre-existing manual stations, both those upgraded to automatic operation and those later decommissioned. I restrict the comparison to existing station locations rather than all pixels within a prefecture. Stations cannot be sited on any arbitrary 30 × 30 m pixels: feasibility depends on infrastructure, land use restrictions, and access constraints not observed at comparable resolution. Existing station locations provide a more defensible, and also more conservative, set of plausible alternatives.

The coefficient of interest β captures whether pixels designated as new station sites exhibit systematically higher levels of vegetation density than manual sites, conditional on fixed effects. Because site designation was all announced in 2012 and does not vary over time, identification comes from spatial variation in NDVI across station locations within the same prefecture and year. Prefecture fixed effects θ_k account for time-invariant local characteristics. Year fixed effects η_t absorb common temporal shocks affecting vegetation nationwide, such as national greening campaigns. In some specifications, prefecture-by-year fixed effects further absorb time-varying shocks specific to each prefecture.[59] Several models additionally control for prefecture-level vegetation coverage (NDVI_{kt}), measured using both median and mean NDVI values.

The results show a systematic correlation between vegetation density and the spatial distribution of newly built monitoring stations during the automation rollout. Table 1 presents estimates from increasingly saturated specifications. The baseline model (Model 1) includes only NDVI as a predictor and shows no systematic association. Once fixed effects are introduced in Models 2 through 4, the NDVI coefficient becomes positive and statistically significant: new station sites are located in greener microenvironments than manual stations within the same prefecture and year. This pattern remains stable when prefecture-level vegetation coverage controls[60] are added as controls in Models 5 and 6. Across specifications, a one-unit increase in pixel-level NDVI is associated with an approximately 11 percentage point higher likelihood that the pixel is a designated new station site. The pattern is consistent with strategic site selection aimed at lowering reported pollution levels.

5.3 Alternative Explanation I: Administrative efficiency

5.3.1 Site Selection

One possibility is that post-automation stations appear "greener" simply because local governments preferred sites that were administratively convenient—accessible, secure, and straightforward to maintain. Such locations also tend to be in more stable environments and farther from industrial parks, which matters in a context of rapid urban development in China.[61] This explanation does not rule out

[59] Bai (2009).

[60] Prefecture-level NDVI is derived using Google Earth Engine's median and mean reducers.

[61] China's *Technical Regulation for Selection of Ambient Air Quality Monitoring Stations* (HJ 664-2013) (2013) specified five guiding principles for the national monitoring network. One of them, *Comparability*, placing stations in environments that remain stable over time. The five principles are: (1) *Representativeness*: the monitoring stations should objectively reflect the level of and change in air quality within a certain area; they also should assess the impact of pollution sources

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
NDVI	-0.024	0.093	0.095	0.145	0.114	0.116
	(0.109)	(0.043)	(0.044)	(0.072)	(0.051)	(0.052)
NDVI Area (Median)					-0.078	
					(0.034)	
NDVI Area (Mean)						-0.088
						(0.038)
Pref. FE		✓	✓	✓	✓	✓
Year FE			✓	✓	✓	✓
Pref. x Year FEs				✓		
R-squared	0	0.78	0.78	0.781	0.777	0.777
Adjusted R-squared	0	0.774	0.774	0.71	0.771	0.771
Observations	12,398	12,398	12,398	12,398	12,154	12,154

Table 1: Linear Probability Model Estimates of the Correlation Between Vegetation Density and New Station Site Selection, 2008-2016. Coefficient estimates are reported with robust standard errors clustered at the prefecture level in parentheses.

strategic siting: a location can be both administratively convenient and likely to yield favorable readings. The key question is which consideration dominated when these two objectives came apart.

This distinction generates observable implications. If favorable readings drove site selection, new stations should appear in cleaner environments even when doing so required additional coordination or additional infrastructure. If administrative convenience instead dominated, new stations should cluster in accessible locations even when those sites were more likely to produce unfavorable readings.

Three site types serve as useful conceptual benchmarks for this tradeoff. First, Government-affiliated buildings come closest to satisfying both objectives. In the Chinese context, such buildings are often located in relatively open, cleaner areas—sometimes surrounded by vegetation—due to historical siting patterns and governments' preferential access to urban land. They are also easy for local governments to

on air quality and meet the needs of providing the public with health guidelines on air conditions; (2) *Comparability*: the surrounding environmental conditions should be as constant as possible, so that the data collected by each monitoring station are comparable; (3) *Integrity*: urban site conditions should be assessed in terms of their broader environmental context, including such aspects as city geography and meteorology, industrial production layout, and social and economic variables like population distribution; the sites should represent the present condition and a developing air quality trend in the city's primary functional areas, as well as its major air pollution sources; (4) *Forward-looking*: the layout of monitoring sites should be considered in conjunction with city and rural development planning to ensure that the chosen monitoring points can anticipate future urban and rural spatial pattern change tendencies; and (5) *Stability*: once the location of the monitoring sites is determined, it is important not to alter the monitoring point's position in principle, since this would jeopardize the continuity and comparability of the monitoring data.

access and manage. Second, parks represent locations where readings are likely to be most favorable, but they often require additional infrastructure investment to meet technical specifications such as sensor elevation and security, making them administratively costly. Third, Industrial compounds, especially those owned by state-owned enterprises, sit at the opposite end: pollution levels tend to be higher, but administrative access is easier due to state ownership and existing institutional ties (see SI Section B.1.4).

I assess these implications using the information encoded in station names, which often indicate the type of site where a station is located. Figure 5 classifies stations by location type and suggests a consistent hierarchy after automation: government-affiliated buildings are the most common sites, followed by parks, and then factories. This ordering tracks the conceptual tradeoff outlined above. The prevalence of government-affiliated buildings is consistent with administrative convenience. But the prominence of parks—despite their higher coordination and infrastructure costs—suggests that ease of implementation alone cannot account for site selection. Local governments appear to value administrative convenience but do not treat it as the sole objective.

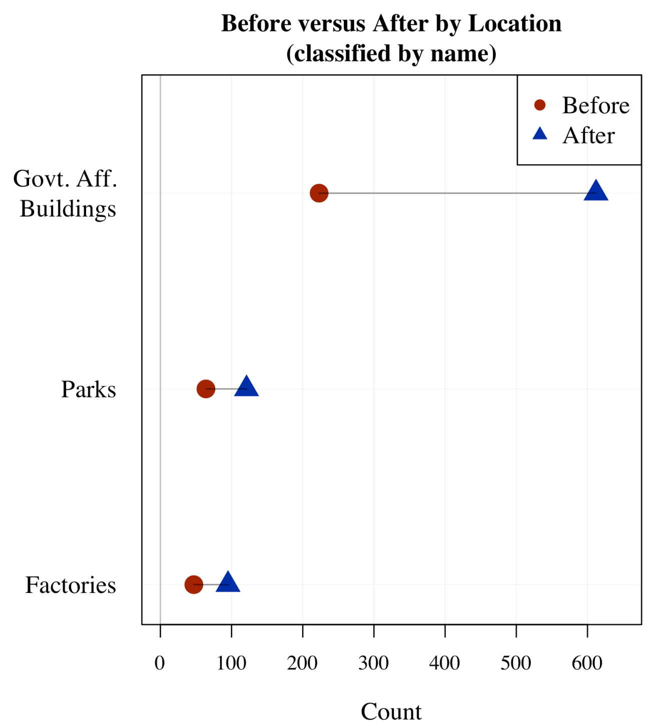


Figure 5: Observed distribution of monitoring station location types before and after automation.

5.3.2 After Installation

Administrative efficiency explanations also imply that government intervention should largely end once stations are installed. If local governments primarily seek to minimize effort, they have little incentive to actively manage conditions around monitoring sites after deployment. Yet local intervention frequently extends well beyond initial site selection in ways that require substantial ongoing coordination.

Consider Mr. Liu, a fried chicken restaurant owner in Handan, Hebei province, whose business license application was denied. When he complained to the mayor's hotline about the investment losses this would impose, officials told him that "all restaurants in the urban area and those involving oil fumes are not allowed to apply for licenses." This was not true—other catering businesses received approvals during the same period. The actual restriction was more targeted: Handan's Bureau of Ecology and Environment (BEE) was specifically rejecting catering businesses located within a 500-meter radius of the three air quality monitoring stations in the national network. Any restaurant falling within this "sensitive zone" would not have its application processed. This practice was unlawful. In 2021, the Eighth State Supervision of the State Council exposed this case and abolished the local regulation.[62]

Handan was not unusual. In many prefectures, local governments deployed mist cannons around monitoring stations to artificially suppress pollution levels.[63] These are not the actions of governments minimizing administrative input. They are the actions of governments strategically managing the microenvironment of automatic reporting.

5.4 Alternative Explanation II: Population Density

A second alternative explanation is population density. Monitoring stations may be located in cleaner areas simply because those areas are also where most people live or visit. Or, residents in relatively clean neighborhoods—who often have higher incomes and stronger political connections—may be more effective at demanding monitoring stations in their communities. Existing research shows that citizen demand can influence policy implementation,[64] making this a plausible hypothesis.

[62] Li (2021); National Development and Reform Commission (2021).
[63] See China News's report here (2018) and Caixin's report here (2022).
[64] Distelhorst and Hou (2017); Tsai and Xu (2018); Anderson et al. (2019); Buntaine et al. (2024).

Demand-driven siting can coexist with strategic design, and I cannot rule out this explanation for the siting study alone. I therefore evaluate this possibility using a more granular breakdown of station site categories in both total number and percentage change in station locations (SI Figure B.3). If siting decisions primarily reflected where people *live*, we would expect the largest increases in residential areas. Residential neighborhoods, however, do not increase after automation. If siting decisions were driven mainly by where people *visit*, we would also expect locations such as parks, schools, and hospitals to increase more than government buildings. Government compounds are often gated and are generally less frequently visited by the public than parks, schools, or hospitals. Yet the data show the opposite pattern. Stations located at government buildings account for the largest increase after automation. Anecdotal cases point in the same direction. Many stations are located inside large parks, scenic areas, or spacious university campuses that are distant from residential neighborhoods. The Agricultural Exhibition Hall station (the purple marker in Figure 4), for example, sits inside a 106-acre park, far from the residential areas where citizens would most plausibly demand monitoring. The shift toward greener sites after automation does not appear to solely to a a shift toward "where people are."

6 Study 3: Station Shutdowns During Pollution Spikes

6.1 Counterfactual

Strategic configuration operates through the day-to-day operation of automatic monitoring stations. The national monitoring network mandates continual data collection, but technical guidelines permit periodic downtime for maintenance and upgrades.[65] This officially sanctioned flexibility serves technical needs, but also creates opportunities for strategic interruptions. Because local officials control maintenance schedules, they can time downtime to coincide with poor air quality episodes—keeping extreme readings out of the average while retaining plausible technical justifications. This leads to the third empirical hypothesis:

Hypothesis 3 Stations experience more downtime during severe pollution episodes.

[65] Automatic monitoring requirements are fulfilled if stations operate 18-20 hours daily for at least 324 days annually (Ministry of Environmental Protection 2012*a*; Ministry of Ecology and Environment 2021; Ministry of Environmental Protection 2013).

To investigate the causal effect of pollution on station operation, I exploit a series of consecutive smog episodes that struck eight northern Chinese provinces in November-December 2015.[66] These extreme pollution events were driven by El Niño-induced warmer temperatures that inhibited pollutant dispersion,[67] rather than by local policy or economic shocks. This provides a quasi-experimental setting. I compare station downtime in affected prefectures with unaffected ones during the same period.

6.2 Data

I compiled the hourly readings of all monitored items from all monitoring stations for February through December 2015 using data archived at https://quotsoft.net/air/.[68] January was excluded due to another major pollution event in northern China.[69] The dataset covers 336 prefectures over 11 months, with 83 prefectures affected by the pollution event and 253 serving as controls. The analysis period includes nine pre-exposure months and two post-exposure months.

For each of the six monitored pollutants, I calculate the missing data proportion in prefecture i on day t as:

$$\text{Missing proportion}_{it} = \frac{\sum_{j=1}^{J_{it}} \sum_{h=1}^{24} \mathbf{1}_{\text{Missing}}(\text{Reading}_{jhit})}{J_{it} \cdot 24} \times 100$$

where j indexes station, and h indexes hours. J_{it} therefore represents the total number of monitoring stations operating in prefecture i and day t. The indicator function $\mathbf{1}_{\text{Missing}}$ equals 1 if the hourly reading from station j in prefecture i in day t at hour h is missing, and 0 otherwise. The formula calculates the percentage of missing hourly records across all stations in prefecture i on day t. The measure missing proportion$_{it}$ ranges from 0 (complete coverage) to 100 (all readings missing). Because daily data exhibit considerable volatility, I aggregate the data to the prefecture-month level, using the unweighted monthly average of daily missing proportions as the outcome variable.

[66] See Xinhua News Agency's report 2015*a*; 2015*b*. The provinces are Beijing, Tianjin, Hebei, Shanxi, Shaanxi, Shandong, Anhui, and Henan.

[67] Yuan, Zhou and Li (2017); Ministry of Environmental Protection (2016).

[68] This is a publicly available archive. Other scholars have used this data set for research, Turiel and Kaufmann (2021, e.g.,).

[69] Ministry of Environmental Protection (2016).

6.3 Empirical Strategy & Results

I estimate the causal effect of extreme pollution on monitoring interruptions using a synthetic difference-in-differences (SDID) estimator.[70] SDID is an estimation strategy that combines difference-in-differences (DID) and synthetic control methods. The method re-weighs the control units so that the pre-exposure trends are approximately parallel to the treated, then applies the DID analysis to the re-weighted panel, focusing on a subset of pre-exposure time periods with non-zero weights (see SI Section C.2).

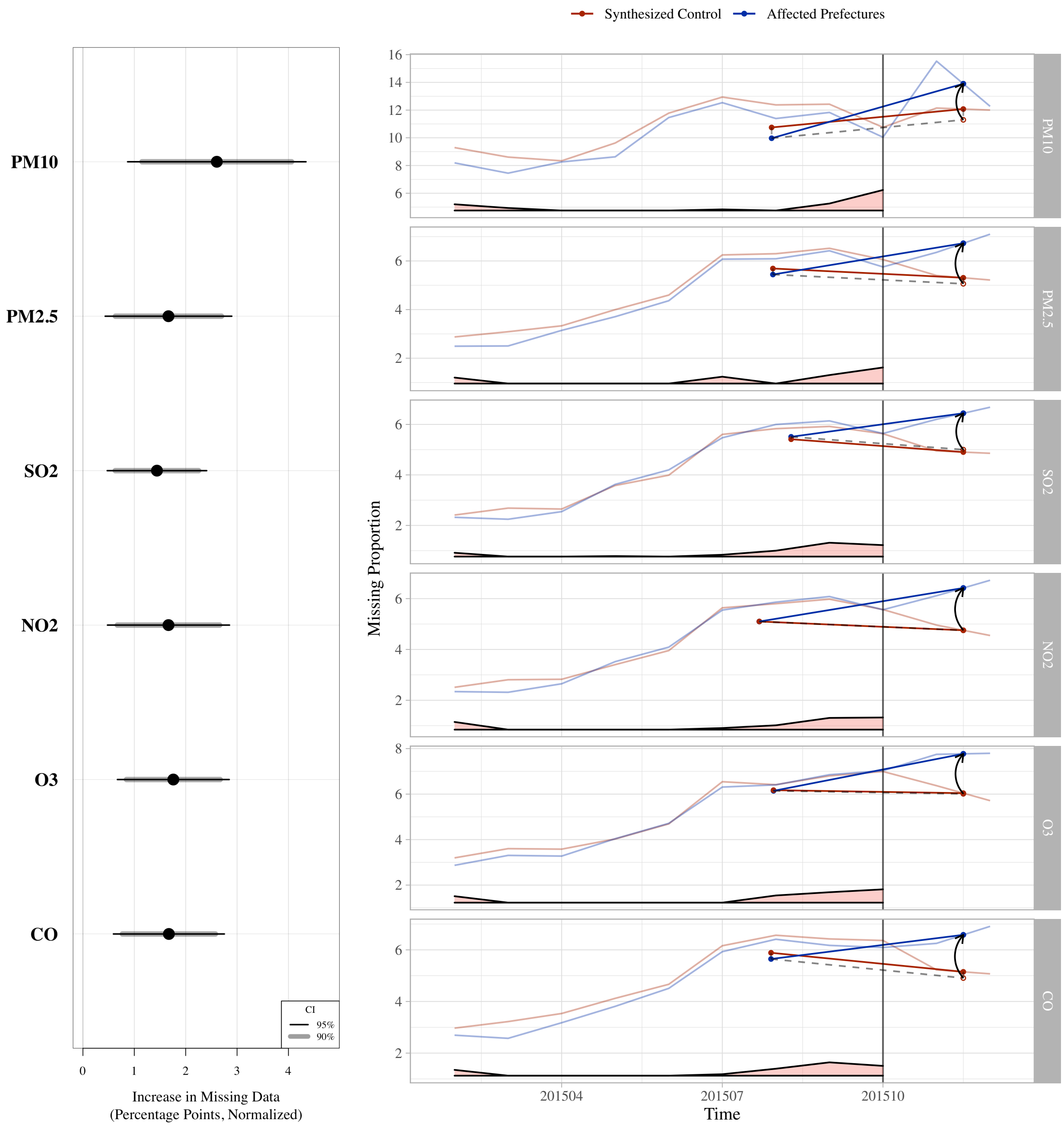
The results show that more polluted prefectures experienced higher rates of monitoring interruption (Figure 6). Panel (a) shows SDID estimates across all six pollutant types: prefectures hit by severe smog events have approximately 2 percentage points more missing readings than unaffected areas, with consistent patterns across all pollutant types. Panel (b) illustrates this effect by comparing trends in missing data between affected prefectures and the weighted average of control prefectures, with weights shown at the bottom. The vertical arrow indicates the estimated treatment effect, which corresponds to the coefficient estimates on the left.

6.4 Alternative Explanation: Technical Necessity

Severe pollution places unusual maintenance demands on monitoring systems: sensors may require more frequent calibration, test strips may need replacement to maintain accuracy at high concentrations, and maintenance teams may face staffing constraints that disrupt routine servicing. The 2015 episode also coincided with the early stages of the national automation rollout, when equipment may not yet have been fully stress-tested at scale. On its own, the observed pattern of missing data cannot distinguish between strategic and technical explanations.

This pattern becomes more informative, however, when viewed alongside the other two studies. Technical necessity can account for non-random missingness during pollution episodes, but it cannot explain why stations are systematically sited in cleaner microenvironments or why coverage gaps are larger in more polluted areas. Likewise, while any single dimension may have alternative explanations,[71] the evidence across all three studies points to a coherent strategic logic. Taken together, strategic

[70] Arkhangelsky et al. (2021).
[71] Spirling and Stewart (2022).



(a) SDID Estimates

(b) SDID Plots

Figure 6: Synthetic difference-in-differences (SDID) analysis of missing air quality readings during pollution events.

Note: (a) Coefficient estimates across all monitored pollutant types: Particulate Matter (PM_{10}; diameter less than 10 micrometers), Fine Particulate Matter ($PM_{2.5}$; diameter less than 2.5 micrometers), Sulfur Dioxide (SO_2), Nitrogen Dioxide (NO_2), Ozone (O_3), and Carbon Monoxide (CO). Thin black and thick gray lines indicate 95% and 90% confidence intervals, respectively, calculated using the placebo method. (b) Temporal trends in missing data proportions comparing affected prefectures (blue line) with a weighted average of unaffected prefectures (red line). The bottom area displays weights used for synthetic control construction in pre-treatment periods. Arrows indicate the estimated treatment effect corresponding to coefficient plots.

configuration provides the most consistent explanation for the full set of findings: it accounts for why fewer stations operate in heavily polluted areas, why new stations are disproportionately located in cleaner locations, and why station downtime increases during severe pollution events.

7 Conclusion

Automation is often celebrated for replacing human discretion with standardized, mechanical rule application. But this is only half of the story. Automation does not eliminate political discretion; it reorganizes it—constraining discretion at the application stage while reallocating it upstream to system design. The empirical analysis shows how this reallocation operates in practice. Across three dimensions of China's automated air quality monitoring network, the evidence is consistent with strategic design choices: station coverage, geographic placement, and operational patterns. Monitors are underdeployed in polluted areas, disproportionately sited in greener locations, and experience more downtime during pollution spikes. These patterns suggest that the most consequential exercises of political discretion may also be the least visible.

The welfare implications of automated governance remain unclear but increasingly important. Existing research has warned that automated systems can reproduce and amplify social, economic, and racial inequalities through biased training data, opaque algorithms, and institutional neglect.[72] China's automation initiative complicates this account. Systematically biased public information can still be informative when its distortions are stable and predictable over time. Even when the numbers do not perfectly reflect reality, their consistency makes it possible to track changes over time.[73] Presenting air quality as somewhat better than reality may reduce public pressure, creating political space for longer-term planning—insulating leaders from the adverse effects of short-term demands and local interests.[74] It may also reduce the intense scrutiny that drives performative responses and diverts already scarce frontline resources.[75] China's recent environmental trajectory is consistent with this logic. Since 2014,

[72] E.g., Eubanks (2018); Obermeyer et al. (2019); Engstrom and Ho (2020); Benjamin (2023).
[73] Liu (2026).
[74] Malesky, Schuler and Tran (2012).
[75] Ding (2020).

the country has achieved substantial improvements in air quality through the "war on pollution."[76] It has strengthened environmental regulations and enforcement, and undertaken real local efforts to combat pollution.[77] These developments have occurred alongside parallel monitoring systems, including direct emission and internal networks, that provide more granular data to regulators while remaining inaccessible to the public.[78] The result resembles a dual-track approach to automated governance: strategically managing public-facing information while relying on internal data that more accurately captures pollution levels to guide targeted enforcement.

Beyond what automated systems deliver, an equally important question is what they mean for democratic accountability. In principle, democratic institutions like elections, independent oversight bodies, and a free media can scrutinize how automated systems are built and deployed. In practice, many government operations remain too opaque for public scrutiny, too technical for effective oversight, or too mundane to attract sustained attention.[79] These limitations create space for strategic design in democratic contexts as well. China illustrates the logic in stark form: political authorities face few constraints on system design, and automation shields the exercise of discretion upstream, wrapping strategic choices in the appearance of neutral, mechanical governance. But the underlying dynamic is not uniquely authoritarian. As automation spreads across policy domains and political systems, the question this paper raises becomes more pressing: how do states govern when exercising discretion is politically and administratively costly? The theory developed here suggests that discretion migrates upstream and becomes concentrated among a smaller group of political actors who shape information at its source. Whether accountability mechanisms can follow it there—and how societies respond when they cannot—remain open questions.

[76] Greenstone et al. (2021).
[77] Ding (2022); Van der Kamp (2023); Shen (2022).
[78] Buntaine et al. (2024).
[79] E.g., Lowande (2018); Ban and Hill (2023).

References

Alkon, Meir and Erik H Wang. 2018. "Pollution Lowers Support for China's Regime: Quasi-Experimental Evidence from Beijing." *The Journal of Politics* 80(1):327–331.

Anderson, Sarah E, Mark T Buntaine, Mengdi Liu and Bing Zhang. 2019. "Non-Governmental Monitoring of Local Governments Increases Compliance with Central Mandates: A National-Scale Field Experiment in China." *American Journal of Political Science* 63(3):626–643.

Aragão, Roberto and Lukas Linsi. 2022. "Many Shades of Wrong: What Governments Do When They Manipulate Statistics." *Review of International Political Economy* 29(1):88–113.

Arkhangelsky, Dmitry, Susan Athey, David A Hirshberg, Guido W Imbens and Stefan Wager. 2021. "Synthetic Difference-in-Differences." *American Economic Review* 111(12):4088–4118.

Baca-López, Karol, Cristóbal Fresno, Jesús Espinal-Enríquez, Mireya Martínez-García, Miguel Angel Camacho-López, Miriam V Flores-Merino and Enrique Hernández-Lemus. 2021. "Spatio-Temporal Representativeness of Air Quality Monitoring Stations in Mexico City: Implications for Public Health." *Frontiers in public health* 8:536174.

Bai, Jushan. 2009. "Panel Data Models with Interactive Fixed Effects." *Econometrica* 77(4):1229–1279.

Ban, Pamela and Seth J Hill. 2023. "Efficacy of Congressional Oversight." *American Political Science Review* pp. 1–19.

Barwick, Panle Jia, Shanjun Li, Liguo Lin and Eric Yongchen Zou. 2024. "From Fog to Smog: The Value of Pollution Information." *The American Economic Review* 114(5):1338–1381.

Benjamin, Ruha. 2023. Race after Technology. In *Social Theory Re-Wired*. Routledge pp. 405–415.

Beraja, Martin, Andrew Kao, David Y Yang and Noam Yuchtman. 2023. "AI-tocracy." *The Quarterly Journal of Economics* 138(3):1349–1402.

Berliner, Daniel. 2014. "The Political Origins of Transparency." *The journal of Politics* 76(2):479–491.

Brambor, Thomas, Agustín Goenaga, Johannes Lindvall and Jan Teorell. 2020. "The Lay of the Land: Information Capacity and the Modern State." *Comparative Political Studies* 53(2):175–213.

Brombal, Daniele. 2017. "Accuracy of Environmental Monitoring in China: Exploring the Influence of Institutional, Political and Ideological Factors." *Sustainability* 9(3):324.

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):815–850.

Burgess, Robin, Matthew Hansen, Benjamin A Olken, Peter Potapov and Stefanie Sieber. 2012. "The Political Economy of Deforestation in the Tropics." *The Quarterly journal of economics* 127(4):1707–1754.

Cao, Xun, Genia Kostka and Xu Xu. 2019. "Environmental Political Business Cycles: The Case of PM2.5 Air Pollution in Chinese Prefectures." *Environtal Science & Policy* 93:92–100.

CCTV.NET. 2021. "Ministry of Ecology and Environment: Over Three Million Fixed Pollution Sources Nationwide Are Included in the Pollutant Discharge Portal.".

China National Environmental Monitoring Centre. 2014. "The Purpose of Regional Station Construction and the Principle.".

Cook, Scott J and David Fortunato. 2023. "The Politics of Police Data: State Legislative Capacity and the Transparency of State and Substate Agencies." *American Political Science Review* 117(1):280–295.

Ding, Iza. 2020. "Performative Governance." *World Politics* 72(4):525–556.

Ding, Iza. 2022. *The Performative State: Bureaucrats and Citizens in China's Environmental Governance*. Cornell University Press.

Distelhorst, Greg and Yue Hou. 2017. "Constituency Service under Nondemocratic Rule: Evidence from China." *The Journal of Politics* 79(3):1024–1040.

Donaldson, Dave and Adam Storeygard. 2016. "The View from Above: Applications of Satellite Data in Economics." *Journal of Economic Perspectives* 30(4):171–198.

Duyzer, Jan, Dick van den Hout, Peter Zandveld and Sjoerd van Ratingen. 2015. "Representativeness of Air Quality Monitoring Networks." *Atmospheric Environment* 104:88–101.

Eckhouse, Laurel. 2021. "Metrics Management and Bureaucratic Accountability: Evidence from Policing." *American Journal of Political Science* .

Engstrom, David Freeman and Daniel E Ho. 2020. "Algorithmic Accountability in the Administrative State." *Yale J. on Reg.* 37:800.

Eubanks, Virginia. 2018. *Automating Inequality: How High-tech Tools Profile, Police, and Punish the poor*. Macmillan+ ORM.

Fowlie, Meredith, Edward Rubin and Reed Walker. 2019. Bringing Satellite-Based Air Quality Estimates Down to Earth. In *AEA Papers and Proceedings*. Vol. 109 American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203 pp. 283–288.

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.

Ghanem, Dalia, Shu Shen and Junjie Zhang. 2020. "A Censored Maximum Likelihood Approach to Quantifying Manipulation in China's Air Pollution Data." *Journal of the Association of Environmental and Resource Economists* 7(5):965–1003.

Grainger, Corbett, Andrew Schreiber and Wonjun Chang. 2019. "Do Regulators Strategically Avoid Pollution Hotspots When Siting Monitors? Evidence from Remote Sensing of Air Pollution." *Department of Economics, University of Wisconsin–Madison Working Paper* .

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.

Greenstone, Michael, Guojun He, Shanjun Li and Eric Yongchen Zou. 2021. "China's War on Pollution: Evidence from the First 5 Years." *Review of Environmental Economics and Policy* 15(2):281–299.

Greitens, Sheena Chestnut. 2020. "Surveillance, Security, and Liberal Democracy in the Post-COVID World." *International Organization* 74(S1):E169–E190.

Guangfa Securities. 2017. "Report on the Environmental Monitoring Industry.".

He, Guojun, Shaoda Wang and Bing Zhang. 2020. "Watering Down Environmental Regulation in China." *The Quarterly Journal of Economics* 135(4):2135–2185.

Hellmeier, Sebastian. 2016. "The Dictator's Digital Toolkit: Explaining Variation in Internet Filtering in Authoritarian Regimes." *Politics & Policy* 44(6):1158–1191.

Herrera, Yoshiko M. and Devesh Kapur. 2007. "Improving Data Quality: Actors, Incentives, and Capabilities." *Political Analysis* 15(4):365–386.

Honig, Dan, Ranjit Lall and Bradley C Parks. 2023. "When Does Transparency Improve Institutional Performance? Evidence from 20,000 Projects in 183 Countries." *American Journal of Political Science* 67(4):1096–1116.

Janhäll, Sara. 2015. "Review on Urban Vegetation and Particle Air Pollution – Deposition and Dispersion." *Atmospheric environment* 105:130–137.

Jerven, Morten. 2013. *Poor Numbers: How We Are Misled by African Development Statistics and What to Do about It*. Cornell University Press.

Karplus, Valerie J and Mengying Wu. 2023. "Dynamic Responses of SO2 Pollution to China's Environmental Inspections." *Proceedings of the National Academy of Sciences* 120(17):e2214262120.

Karplus, Valerie J, Shuang Zhang and Douglas Almond. 2018. "Quantifying Coal Power Plant Responses to Tighter SO2 Emissions Standards in China." *Proceedings of the National Academy of Sciences* 115(27):7004–7009.

King, Gary, Jennifer Pan and Margaret Roberts. 2013. "How Censorship in China Allows Government Criticism but Silences Collective Expression." *American Political Science Review* 107(2 (May)):1–18.

Kintisch, Eli. 2018. "Department of State's air pollution sensors go global." *Science* 360(6386):248–249.

Knox, Dean, Will Lowe and Jonathan Mummolo. 2020. "Administrative Records Mask Racially Biased Policing." *American Political Science Review* 114(3):619–637.

Kostka, Genia. 2016. "Command without Control: The Case of China's Environmental Target System." *Regulation & Governance* 10(1):58–74.

Lancaster, Tony. 2000. "The Incidental Parameter Problem Since 1948." *Journal of econometrics* 95(2):391–413.

Lee, Melissa M. and Nan Zhang. 2016. "Legibility and the Informational Foundations of State Capacity." *The Journal of Politics* (1):118–132. Publisher: The University of Chicago Press.

Li, Xiongying. 2021. "No Smoking Restaurants within 500 Meters of the Air Monitoring Point." *Xinhua News* .

Lin, Tao and Wenhao Qian. 2024. "Water Quality Monitoring and Mortality: Evidence from China." *Applied Economics* 56(24):2819–2835.

Lipsky, Michael. 2010. *Street-level Bureaucracy: Dilemmas of the Individual in Public Service*. Russell sage foundation.

Litschke, Tom and Wilhelm Kuttler. 2008. "On the Reduction of Urban Particle Concentration by Vegetation - A Review." *Meteorologische Zeitschrift* 17(3):229–240.

Liu, Guoer. 2026. "Credible Bias: Why Information Does Not Need to Be Accurate to Be Useful." Working paper.

Lowande, Kenneth. 2018. "Who Polices the Administrative State?" *American Political Science Review* 112(4):874–890.

Lutscher, Philipp M. 2023. "Hot Topics: Denial-Of-Service Attacks on News Websites in Autocracies." *Political Science Research and Methods* 11(4):696–711.

Malesky, Edmund, Paul Schuler and Anh Tran. 2012. "The Adverse Effects of Sunshine: A Field Experiment on Legislative Transparency in an Authoritarian Assembly." *American Political Science Review* 106(4):762–786.

Martinez, Luis R. 2022. "How Much Should We Trust the Dictator's GDP Growth Estimates?" *Journal of Political Economy* 130(10):2731–2769.

Ministry of Ecology and Environment. 2021. "2021 National Ecological Environment Monitoring Program.".

Ministry of Environmental Protection. 2012*a*. Notice on Printing and Distributing the Plan for the Establishment of the National Surface Water and Ambient Air Monitoring Network (Cities Above the Prefectural Level). Technical report.

Ministry of Environmental Protection. 2012*b*. "Technical Regulation on Ambient Air Quality Index (Trial).".

Ministry of Environmental Protection. 2013. "China's Technical Regulation for Selection of Ambient Air Quality Monitoring Stations [Huanjing Kongqi Zhiliang Jiance Dianwei Bushe Jishu Guifan] 2013 (HJ 664-2013).".

Ministry of Environmental Protection. 2016. "2015 China Environmental State Bulletin.".

Monogan III, James E, David M Konisky and Neal D Woods. 2017. "Gone with the Wind: Federalism and the Strategic Location of Air Polluters." *American Journal of Political Science* 61(2):257–270.

Mu, Yingfei, Edward Rubin and Eric Yongchen Zou. 2024. "What's Missing in Environmental Self-Monitoring: Evidence from Strategic Shutdowns of Pollution Monitors." *Review of Economics and Statistics* pp. 1–45.

National Development and Reform Commission. 2021. "Typical Cases of Violation of the Negative List for Market Access and Notification of Handling.".

National Energy Administration. 2020. "All Point Source Pollution in Our Country Will Achieve "One Certificate" Management This Year.".

Neyman, Jerzy and Elizabeth L Scott. 1948. "Consistent Estimates Based on Partially Consistent Observations." *Econometrica: journal of the Econometric Society* pp. 1–32.

Obermeyer, Ziad, Brian Powers, Christine Vogeli and Sendhil Mullainathan. 2019. "Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations." *Science* 366(6464):447–453.

Piersanti, Antonio, Lina Vitali, Gaia Righini, Giuseppe Cremona and Luisella Ciancarella. 2015. "Spatial Representativeness of Air Quality Monitoring Stations: A grid Model Based Approach." *Atmospheric Pollution Research* 6(6):953–960.

Roberts, Margaret E. 2018. *Censored: Distraction and Diversion Inside China's Great Firewall*. Princeton University.

Rohde, Robert A and Richard A Muller. 2015. "Air Pollution in China: Mapping of Concentrations and Sources." *PLoS One* 10(8).

Scott, James C. 1998. *Seeing Like a State: How Certain Schemes to Improve the Human Condition Have Failed*. Yale University Press.

Shen, Shiran Victoria. 2022. *The Political Regulation Wave: A Case of How Local Incentives Systematically Shape Air Quality in China*. Cambridge University Press.

Spirling, Arthur and Brandon Stewart. 2022. "What Good Is a Regression? Inference to the Best Explanation and the Practice of Political Science Research.".

State Environmental Protection Administration. 2007. "Ambient Air Quality Monitoring Standards (Trial).".

Steinhardt, H Christoph and Fengshi Wu. 2016. "In the Name of the Public: Environmental Protest and the Changing Landscape of Popular Contention in China." *The China Journal* 75(1):61–82.

Tang, Xiao, Yinglun Wang and Hongtao Yi. 2022. "Data Manipulation through Patronage Networks: Evidence from Environmental Emissions in China." *Journal of Public Administration Research and Theory* .

Treisman, Daniel and Sergei Guriev. 2023. "Spin Dictators: The Changing Face of Tyranny in the 21st Century.".

Tsai, Lily L and Yiqing Xu. 2018. "Outspoken Insiders: Political Connections and Citizen Participation in Authoritarian China." *Political Behavior* 40(3):629–657.

Turiel, Jesse S and Robert K Kaufmann. 2021. "Evidence of Air Quality Data Misreporting in China: An Impulse Indicator Saturation Model Comparison of Local Government-Reported and U.S. Embassy-Reported PM2.5 Concentrations (2015-2017)." *PLoS One* 16(4).

Van der Kamp, Denise Sienli. 2023. *Clean Air at What Cost?: The Rise of Blunt Force Regulation in China*. Cambridge University Press.

Wallace, Jeremy. 2016. "Juking the Stats? Authoritarian Information Problems in China." *British Journal of Political Science* 46(1):11–29.

Wallace, Jeremy L. 2022. *Seeking Truth and Hiding Facts*. Oxford University Press.

Wang, Alex L. 2013. "The Search for Sustainable Legitimacy: Environmental Law and Bureaucracy in China." *Harvard Environmental Law Review* 37:365.

Xinhua. 2015*a*. "Frequent Smog Weather in Autumn and Winter, Beijing Sounded Heavy Pollution Warning 9 Times in 70 Days.".

Xinhua. 2015*b*. "Smog in North China Has Caused More Than 20 Cities to Start Warnings, and Beijing's Heavy Pollution Will Continue for 3 Days.".

Xu, Xu. 2021. "To Repress or to CO-opt? Authoritarian Control in the Age of Digital Surveillance." *American Journal of Political Science* 65(2):309–325.

Yuan, Yuan, Ning-Fang Zhou and Chong-Yin Li. 2017. "Correlation between Haze in North China and Super El NiñO Events." *Chinese Journal of Geophysics* 60(1):11–21.

Zhang, Jin, Han Xiao, Qingyue He, Jie Peng, Ding Li and Yuan Liu. 2024. "When to Issue the Alert of Air Pollution in Chinese Cities? Evidence on the Threshold Effect of Heavy Air Pollution from Chengdu." *Environmental Impact Assessment Review* 105:107371.

Zhao, Hanping, Fangping Wang, Chence Niu, Han Wang and Xiaoxue Zhang. 2018. "Red Warning for Air Pollution in China: Exploring Residents' Perceptions of the First Two Red Warnings in Beijing." *Environmental research* 161:540–545.

Supplementary Information
“Co-opting Automation: How Technology Reorganizes Political Discretion in China”*

Guoer Liu†

Contents

*Pre-edited version. Forthcoming in *World Politics*, 79, no. 3 (July 2027).
†Assistant Professor, Department of Political Science, University of California, San Diego. Email: guoerliu@ucsd.edu.

A Institutional Context

A.1 12th Five-Year Plan

The Chinese government's 12th Five-Year Plan (2011 - 2016) mandated establishing a "well-equipped and statistical monitoring system" and "index evaluation system" to evaluate progress in environmental governance.[1] In 2012, the national government launched a network of automated monitoring stations. The initiative transformed China's air quality monitoring through three major improvements from the previous manual system: automated data collection, comprehensive and standardized measurement, and real-time public dissemination.

First, standardized and automated technology replaced human labor in data collection, analysis, and dissemination. Each station now performs tasks that local EPA officials and technicians previously handled manually.[2] The stations monitor a standardized set of pollutants—Sulfur Dioxide (SO_2), Nitrogen Dioxide (NO_2), Particulate Matter (PM_{10}), Fine Particulate Matter ($PM_{2.5}$), Carbon Monoxide (CO), and Ozone (O_3)—on an hourly basis following standardized technical specifications. The entire network follows an integrated set of official guidelines, enabling systematic comparison of air quality across locations and over time. These comprehensive measurements would not have been possible under the previous manual, infrequent monitoring practice. Automation also reduces opportunities for data manipulation by standardizing sampling, analysis and reporting procedures that were previously subject to human discretion.[3] This technological standardization marks a fundamental shift in China's environmental monitoring capabilities.

Second, automation dramatically expanded air quality monitoring coverage in China. Before automation, only 113 designated prefectures had their air quality monitored and reported. The expansion to all prefectures occurred through three phases. The initial phase, completed by the end of 2012, focused on major urban centers: the four metropolitan cities (Beijing, Tianjin, Shanghai, and Chongqing), 27 provincial capitals, and all prefectures in key economic regions (the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei area). These areas began using new air quality standards in January 2013. The second phase targeted an additional 116 prefectures with 449 monitoring stations, requiring completion by October 2013 and transitioning to new standards in January 2014. The final phase covered all remaining prefectures, with upgrades completed by November 2014, bringing the total to 1,436 stations. By 2015, the entire network was operational across all prefectures in China. The network continued to grow, reaching approximately 1,800 stations nationwide by 2020.[4]

[1] Hsu, de Sherbinin and Shi (2012).
[2] Cao (2015).
[3] Greenstone et al. (2022).
[4] See *Xinhua News Agency* report here.

Third, the automation initiative transformed how air quality information reaches the public. Under the manual system, only some prefectures published air quality reports weekly in local newspapers, with a few major cities providing daily updates. The automated system now delivers hourly updates from every prefecture through multiple platforms, including websites, mobile apps, and public displays. National guidelines mandate this broad and user-friendly dissemination of data, substantially improving both the frequency and accessibility of air quality information. The official document states that:

> [The information should be] publicized in local and national air quality information portals, mobile device software, Weibo, TV, radio, *et cetera*. [The content should] strive to be simple and straightforward, in various forms, and easily accessible to the public so that they are always informed about the air quality situation in a timely manner. [The information] is meant to improve public health by providing a reference for the public to plan their daily activities and travel.[5]

This new approach to information sharing represents a shift toward transparency in environmental monitoring.

A.2 Targets and Incentives

The specific target for air quality standards is that "prefectures' air quality meets or exceeds the Grade II standard above 80%" (in Chinese "地级以上城市空气质量达到二级标准以上的比例 $\geq$ 80").[6]

A.2.1 Evaluation & Consequences

Performance is evaluated through two mechanisms: a point system that scores prefectures on air quality metrics, and a ranking system that compares standardized pollution levels across prefectures. Importantly, no points are awarded if the data collection process is not automated. This requirement ensures prefectures have automated monitoring systems in place, but does not specify or evaluate the technical details of how automation is implemented.

Both evaluation mechanisms carry tangible regulatory and financial consequences. Since 2012, many cities have adopted an AQI of 200 as the threshold for triggering pollution early warnings, accompanied by a series of contingency plans to alleviate pollution and protect public health.[7] Pollution rankings also enable naming and shaming, as the deputy head of MEE's Department of Pollution Prevention warned: "Mayors, you'll have to answer for this yourselves if you always ranked at the bottom."[8] These reputational pressures are reinforced by material incentives. Some

[5] (The General Office of the Ministry of Environmental Protection 2014, p.8, texts in brackets are mine).
[6] State Council (2011).
[7] Zhao et al. (2018); Zhang et al. (2024).
[8] See *The Beijing News*'s report here.

top performers can receive rewards up to 15 million RMB, funded by fines collected from bottom-ranked localities.[9]

Poor performance can trigger direct intervention from central authorities. During the Beijing Airpocalypse between 2013 and 2015, AQI levels repeatedly maxed out the 500-point scale, with PM2.5 concentration sometimes exceeding 900 micrograms per square meter—about 36 times the WHO's recommended limit.[10] Beijing Mayor Anshun Wang had to sign a mission pledge under the threat that "if the air pollution targets are not met by 2017, your head will roll."[11] Other local officials whose regions ranked at the bottom were regularly summoned to Beijing to explain pollution control failures.[12]

A.2.2 Limited Procedural Oversight

While the General Office of the Ministry of Environmental Protection issued guidelines for assessing monitoring station quality,[13] these guidelines were limited in scope. The evaluation rubric contained only four basic columns (prefecture name, station name, station type, and notes) without additional specifications or requirements. Later guidance stated that "for prefectures where data is missing due to no reason, they will be publicly criticized in the media, and will be counted as having failed the assessment in the air pollution prevention and control action plan evaluation."[14] However, I found no documented cases of prefectures facing public criticism solely for unexplained missing data.

[9] See reports from Guangzhou EPA's website, Heibei EPA's website, *Shanxi Daily*.
[10] See Reuter's report here.
[11] See *China Economic Weekly*'s report on Feb 11, 2014.
[12] See reports from Xinhua News Agency, *CCTV-news*, and *Economic Daily*.
[13] General office of the Ministry of Environmental Protection (2012).
[14] General Office of Ministry of Ecology and Environment (2018, p.5).

B Data

B.1 Monitoring Stations

B.1.1 Identifying Monitoring Stations

This study establishes a comprehensive geo-referenced panel dataset of air quality monitoring stations in China spanning from 2008 to 2021. The dataset focuses on stations officially recognized as urban assessment stations, which are responsible for monitoring air quality trends in urban built-up areas. For each station, I collected six essential variables: station ID, station name, prefecture, longitude, latitude, and a reference station indicator that distinguishes stations used solely for technical quality control from those used in official air quality assessments.

The construction of this dataset required linking multiple official sources. For the post-2012 automatic network, the key document is the Ministry of Ecology and Environment's (MEE) "Notice on Printing and Distributing the Plan for the Establishment of the National Surface Water and Ambient Air Monitoring Network."[15] This document provided a comprehensive list of automatic monitoring stations through 2014. For 2014-2021 data, I obtained data through scraping of station information from https://quotsoft.net/air/, which maintained yearly archives containing all six variables of interest. For the historical period preceding 2012, I accessed two documents from Baidu Library: the "2008 Ambient Air Monitoring Sites in Cities Above Prefecture Level" and the "2006 List of Ambient Air Monitoring Stations in 113 Key Cities."[16]

Since Baidu Library operates as an open-access platform where users can upload documents, I carefully validated its documents against the official MEE document, which provided a detailed account of the network expansion:

> After optimization and adjustment, the national ambient air monitoring network expanded its coverage from 113 key environmental protection prefectures (henceforth key prefectures) to 338 prefectures across 31 provinces, autonomous regions, and municipalities nationwide. The total number of monitoring stations increased from 661 to 1,436. Specifically, the original 113 key prefectures, which had 661 ambient air quality monitoring stations, underwent the following changes: 59 cities participated in the adjustment, resulting in 77 new stations, 42 relocated stations, and 30 decommissioned stations. After these adjustments, the 113 key prefectures contained 708 ambient air quality monitoring stations. The remaining 225 prefectures, which were newly incorporated into the network, added 728 state-controlled ambient air quality monitoring stations.

[15] Ministry of Environmental Protection (2012).

[16] Baidu Library (2008, 2006).

The initial examination revealed significant discrepancies in both Baidu Library documents. The 2008 document contained 1,352 stations, approximately double the 661 stations cited in the 2012 official document. Two potential explanations for this discrepancy. First, the higher count might include stations that were still in the planning phase, as the national government had begun developing new monitoring plan in 2008.[17] Second, the count might have incorporated stations from non-key prefectures that operated outside the national network. The 2006 document listed only 627 stations—below the official figure—but it proved valuable for a different reason: it contained a complete list of the 113 key prefectures. When I used this list to filter stations in the 2008 document, retaining only those located in key prefectures, I extracted exactly 661 stations. This number matched precisely with the official count reported in the 2012 MEE document, confirming the accuracy of our filtering approach. The resulting validated dataset of 661 stations across 113 key prefectures established the pre-automation prefecture-station table.

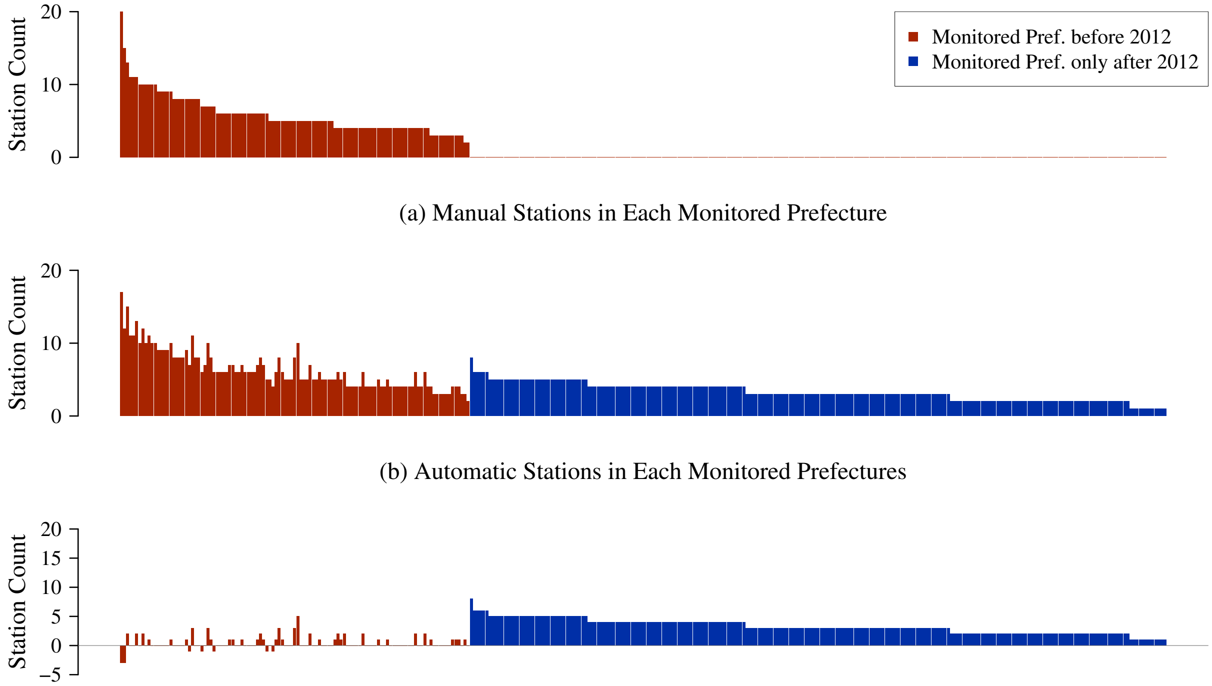
To track individual stations across data sources and time periods, I exploited a regulatory requirement: environmental regulations in China strictly prohibit the relocation or renaming of monitoring stations, whether manual or automatic.[18] Each station therefore maintains fixed geocoordinates throughout its operational lifetime. I used the combination of prefecture and station name as a unique identifier to link station records across documents and fill in missing information. In rare cases where station names showed inconsistencies due to typographical errors or minor variations, I relied on station IDs as an alternative identification method.

Figure B.1 compares the number of stations before and after 2012 at the prefecture level. Panel (a) depicts the pre-2012 network, with red bars showing the number of stations in each of the 113 prefectures, arranged in descending order for clarity. At this stage, the national network comprised 661 stations distributed across these prefectures. Panel (b) shows the network's expansion after 2012, where blue bars indicate prefectures newly incorporated into the system. The network grew substantially to include 1,436 stations spanning all 338 prefectures in China. In Panel (c), I track changes in station numbers for individual prefectures. While the original 113 prefectures generally maintained stable station counts, some experienced minor adjustments. For example, Chongqing and Beijing—two provincial-level municipalities—each decommissioned three monitoring stations after automation. The most substantial expansion came from incorporating 225 new prefectures that previously had no systematic air quality monitoring.

B.1.2 Measure Station Shortage

The minimum number of required monitoring stations for each prefecture is determined by China's "Technical Regulation for Selection of Ambient Air Quality Monitoring Stations" (HJ 664-2013).[19]

[17] Lifeweek (2014).
[18] Ministry of Environmental Protection (2013); State Environmental Protection Administration (2007).
[19] Ministry of Environmental Protection (2013).



(a) Manual Stations in Each Monitored Prefecture

(b) Automatic Stations in Each Monitored Prefectures

(c) Differences in Each Monitored Prefectures

Figure B.1: Comparing Station Count by Prefectures up to 2014.

The regulation establishes requirements based on two metrics—urban population and built-up area size—as specified in the following directive:

> The minimum number of monitoring locations for evaluating urban air quality in each city should meet the requirements of Table B.1. When the minimum number of monitoring locations determined by the urban population and the built-up area size are different, the larger of the two values should be taken.

Population in urban built-up area (10,000 ppl)	Urban built-up area (km^2)	Minimum number of monitoring stations
<25	<20	1
25 - 50	20 - 50	2
50 - 100	50 - 100	4
100 - 200	100 - 200	6
200 - 300	200 - 400	8
>300	>400	Set up one monitoring station for every 50-60 km^2 of built-up area, with no fewer than 10 stations in total.

Table B.1: Requirement for the Number of Monitoring Stations.

Using this regulatory formula as a reference point, I calculated the gap between each prefecture's expected and actual number of monitoring stations in 2020. This difference (expected minus actual stations) serves as my dependent variable in Study 1: positive values indicate a station shortage relative to the regulatory benchmark, while negative values represent a surplus.

B.1.3 Station Coordinates

To establish precise station locations, I used the 2022 coordinates as my baseline due to their superior precision: four decimal points compared to one to three decimal points in earlier years. I validated these coordinates with two methods: visual verification through Google Earth street view and cross-referencing against the Guangdong Province Ecological Environment Monitoring Plan.[20] This document is the only available official document containing coordinate information that I found. The coordinates from the Guangdong document matched exactly with my 2022 data, confirming their accuracy.

I developed additional identification strategies for two special occasions. First, I needed alternative sources for stations decommissioned before 2022, as their coordinates were not included in the 2022 dataset. Second, some stations required extra attention due to spelling variations in their Chinese names. While the combination of prefecture and station names uniquely identifies each station, spelling variations occasionally appear across different documents. These variations include dropping administrative unit designations (e.g., "Longquan zhen" where "zhen" means township, appearing as just "Longquan"), omitting geographic qualifiers (e.g., "Qvwei Dangxiao" where "Qvwei" refers to the district, appearing as just "Dangxiao"), or using alternative Chinese characters with identical pronunciations (e.g., "Hongbianmen" written as either 红边门 or 鸿边门). For these cases, I either standardized the names using the official document[21] or employed station IDs from https://quotsoft.net/air/ as unique identifiers.

B.1.4 Types of Station Locations

Section 5.3 frames station siting as a constrained optimization problem where political actors balance two objectives: minimizing administrative effort in station siting while obtaining favorable air quality readings. In Figure B.2, the top-right quadrant illustrates a key trade-off: state-owned enterprises (SOEs) offer easily accessible sites but present unfavorable measurement conditions. Because SOEs in China primarily operate in pollution-intensive industries such as energy, mining, and steel production, monitoring stations near their facilities are likely to record high pollution levels.

The bottom-left quadrant illustrates an opposite case: parks. According to technical specifications, sensors must be mounted between 3 to 20 meters off the ground[22] and a 20-meter radius surrounding each sensor must be restricted to visitors.[23] This requirement often necessitates the construction of costlier two-story structures and additional efforts to establish utility and internet

[20] Guangdong Department of Ecology and Environment (2020).
[21] Ministry of Environmental Protection (2012).
[22] Ministry of Environmental Protection (2013).
[23] The General Office of the Ministry of Environmental Protection (2017).

Motivation		Cost-Effective Implementation	
		No	Yes
Produce Favorable Readings	No		State owned enterprises
	Yes	Parks	Gov't-affiliated buildings

Figure B.2: Conceptual classification monitoring station location types by administrative cost and expected air quality readings.

connections at park-based stations. Nonetheless, the verdant environment of parks tends to produce lower pollution readings.

Government-affiliated buildings in the bottom-right quadrant satisfy both objectives due to their prime locations and well-connected infrastructure. Establishing a monitoring station on these government-affiliated buildings typically means re-purposing the rooftop to accommodate a single-story structure, which significantly streamlines the administrative process. And because the land is managed by governmental units or institutions affiliated with governments, securing space requires minimal permissions and incurs little costs. Moreover, these locations usually offer reliable utility services and internet connectivity.

Equally important is the fact that public organizations in China are commonly located in less polluted areas. Public schools, nursing homes, and hospitals, catering to serve vulnerable and sensitive groups, are built in areas with abundant greenery. Government office buildings, similarly, are frequently found in cleaner areas. Historically, state-run entities (danwei 单位) enjoyed privileged access to public resources, allowing them to develop gated compounds that many ordinary citizens aspire to live in. Therefore, government-affiliated buildings represent an optimal balance between the two objectives, as evidenced by station locations immediately following the automation initiative.

The primary motivation behind site selection would lead to distinct patterns in location changes after automation. If administrative input is the main factor, we would likely see an increased number of stations in SOEs and government buildings, with parks being less favored. Conversely, if the primary goal is to secure better environmental readings, it is probable that new stations would be predominantly situated in parks and government buildings, with fewer in SOEs. Should the motivations for minimizing effort and favorable readings be equally balanced, the distribution of stations would be consistent across all location types.

To analyze how station locations changed after automation, I exploit the fact that station names often encode information about their physical locations—a relationship I verified using both Baidu Maps and Google Maps. Using a dictionary-based method, I classified stations into location types based on specific terms in their names. For example, stations with names containing government facility references (e.g., "City Hall Station") were classified as government buildings, while those mentioning public spaces (e.g., "People's Park Station") were categorized as parks. When station names lacked clear location indicators (e.g., "State Street Station"), I coded them as unclassified.

The classification system comprises several distinct locations. The "schools" category includes all types of educational institutions: daycares, primary schools, junior and high schools, colleges, and university campuses. For industrial locations, I classify stations as "factories" based on the presence of the Chinese character "厂" (chang, meaning factory) in their names. While I use the term "factories" rather than "State-Owned Enterprises (SOEs)," the character "厂" in Chinese station names typically indicates state ownership, a legacy of China's planned economy era. For example, the Yancheng Power Plant Station (Yancheng Dianchang 盐城电厂) is owned by Jiangsu Guoxin Investment Group Limited and operates under the Jiangsu Provincial Government's State-Owned Assets Supervision and Administration Commission. This association between the character "厂" and state ownership was confirmed through manual verification of ownership records.

Figure B.3 characterizes changes in monitoring station placement following China's air quality monitoring reform. The changes are quantified in two complementary ways: (a) presents the absolute number of stations by location type, while (b) normalizes these counts as percentages of total stations. Among stations with classifiable locations, government-affiliated sites—comprising government buildings, schools, and hospitals—experienced the largest expansion in both absolute numbers and proportional representation. While parks also showed substantial increases, industrial sites exhibited markedly smaller growth compared to government-affiliated locations. Other location types, such as development zones, residential areas and other unclassifed locations remain stable. This systematic relocation pattern, favoring government-affiliated sites over industrial facilities, suggests that political considerations, rather than administrative convenience, may have played a more significant role in determining station placement.

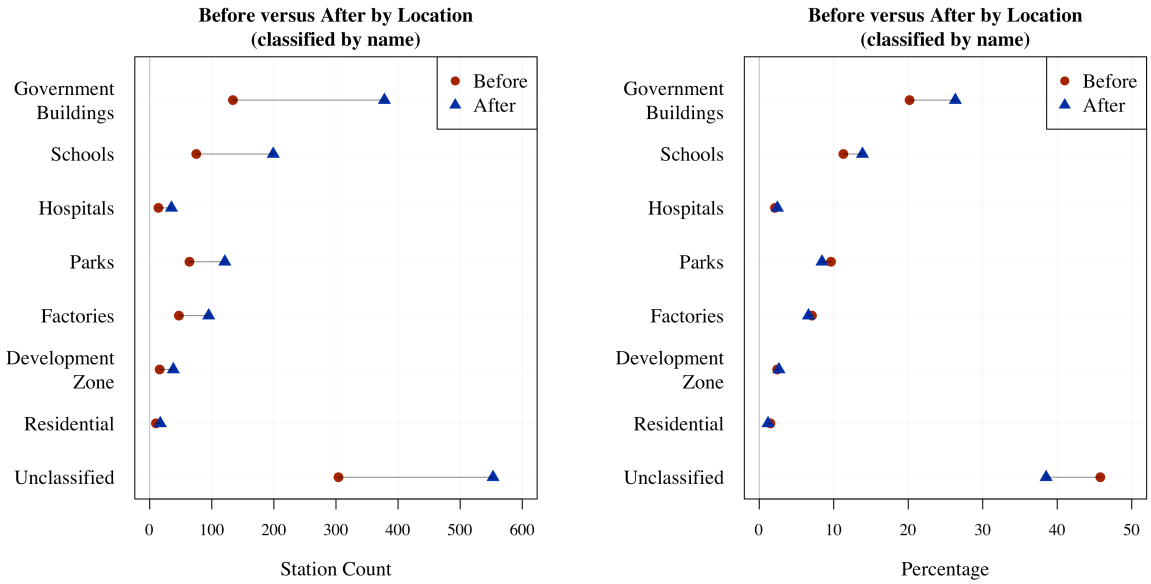
B.2 Pollution Permits

I constructed a dataset of all registered emission permits in China for 2020-2021 by systematically scraping data from the Ministry of Ecology and Environment's (MEE) pollution discharge permit management portal. This permit system has achieved full national coverage of 3.04 million point source polluters by the end of 2020.[24] Note that this system is distinct from China's Continuous Emission Monitoring system that monitors emission concentration from designated key polluters.[25]

The data extraction process spanned from August 25, 2021, to October 2, 2021. The cleaned dataset has 342,866 pollution permits, detailing 24 attributes for each, including the company's name, industrial sector, permit issuance and expiration dates, geocoordinates (longitude and latitude), types of pollutants emitted, and emission frequencies. However, because polluting

[24] National Energy Administration (2020); CCTV.NET (2021).

[25] Buntaine et al. (2024).



(a) Location Change by Count (b) Location Change by Percentage

Figure B.3: Comparing Aggregated Station Location Change Before and After the 2012 Automation Initiative.

firms self-report these data, key variables including pollutant-specific emission levels and discharge frequencies are almost always missing. I therefore use the aggregate count of permits at the prefecture level as a proxy for pollution exposure in the analysis. This measure is admittedly coarse. A count treats a restaurant and an aluminum smelter as equivalent, and an emission-weighted measure would be preferable —but the data do not support one.

Figure B.4 maps the spatial distribution of pollution permits across Chinese prefectures. Using equal-interval breaks, I shade each prefecture according to its total number of permits, with darker colors representing higher concentrations. The resulting pattern reveals a clear spatial correlation with economic development: prefectures in China's southeastern coastal regions, where industrial activity is most intensive, contain the highest density of pollution permits.

B.3 Normalized Difference Vegetation Index (NDVI)

Using NASA's Landsat 7 satellite imagery (30-meter resolution), I constructed two panel datasets of vegetation coverage for 2008-2016, measured by the Normalized Difference Vegetation Index (NDVI). The first dataset captures pixel-level NDVI values at monitoring station locations to analyze station siting patterns. For this dataset, I focused on the peak vegetation season in the northern hemisphere (June 1 to August 31) of each year. Given Landsat 7 satellites orbit Earth on a 16-day cycle, theoretically capturing five images per location each season. I applied Google Earth Engine algorithms to exclude low-quality images affected by cloud cover or poor atmospheric conditions.

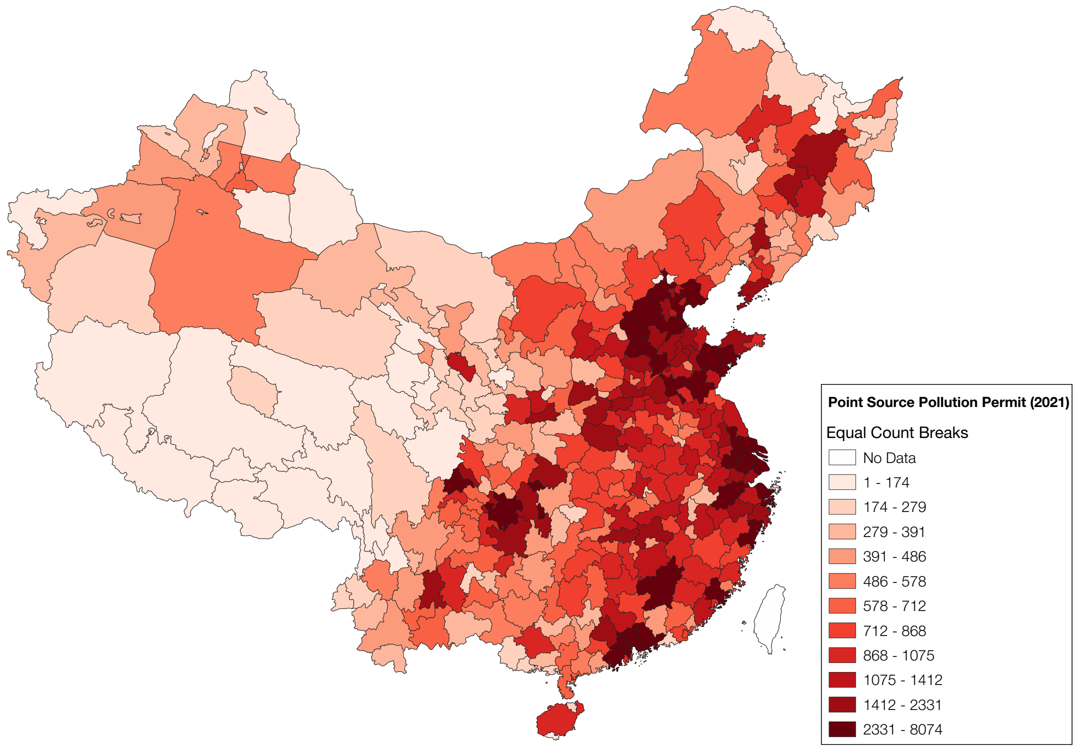


Figure B.4: Geographical Distribution of Point Source Pollution Permits in China in 2021.

The second dataset aggregates NDVI values to the prefecture level, computing both mean and median values through Google Earth Engine. These prefecture-level vegetation measures serve as control variables in some analyses.

B.4 Missing Data

I compiled the hourly readings of all monitored items from all monitoring stations using data archived at https://quotsoft.net/air/ for February through December 2015. January was excluded due to a major pollution event in northern China.[26] The dataset covers 336 prefectures over 11 months, with 83 prefectures affected by the pollution event and 253 serving as controls. The analysis period includes nine pre-exposure months and two post-exposure months. For each of the six monitored pollutants, I calculate the missing data proportion in prefecture i on day t as:

$$\text{Missing proportion}_{it} = \frac{\sum_{j=1}^{J} \sum_{h=1}^{H} \mathbf{1}_{\text{Missing}}(\text{Reading}_{jhit})}{J_{it} \cdot 24} \times 100$$

where J_{it} is the total number of monitoring stations in prefecture i and day t, and H denotes the total monitored hours of the day. The quantity is the missing data proportion of all possible hourly

[26] Ministry of Environmental Protection (2016).

records in all monitoring stations in prefecture i and day t. Therefore, missing proportion$_{it}$ $\in$ $[0, 100]$: 100 means that all readings in all stations in prefecture i and day t are missing, and 0 suggests none is missing. Then, I aggregate the data to calculate the prefecture-month *missing average* for each pollutant, using it as the outcome variable. This approach is chosen due to the considerable fluctuation in the prefecture-day data, rendering it unsuitable for analysis.

C Analysis

C.1 Study 1: Station Coverage Gaps

The most complete OLS regression model specification is as follows,

$$f(\text{Population}_i, \text{Built-up Area}_i) - \text{Actual}_i = \alpha + \beta \text{Pollution}_i + \lambda_j + \epsilon_i \tag{1}$$

where f is the formula in the official document.[27] Population$_i$ and Built-up Area$_i$ are the population and built-up area in prefecture i in 2020, respectively. Actual$_i$ is the number of observed stations in prefecture i as of January 1, 2021. Pollution$_i$ is the number of pollution permits in i in 2021. λ_j is the province fixed effects for province j.

I employed several strategies to address the inherent limitations of analyzing cross-sectional data with high observational variance. To ensure robust statistical inference, I calculated HC2 (Heteroskedasticity-consistent) robust standard errors, which provide more conservative estimates when observations exhibit varying levels of variability. To improve estimation efficiency, I implemented weighted least squares (WLS) regression, which assigns higher weights to observations with lower variance and lower weights to those with higher error variance. I further tested the robustness of results across different sample specifications: a) all monitoring stations b) excluding reference stations (whose readings are not evaluated) c) restricting to non-capital prefectures This multi-sample approach helps control for potential biases arising from specific station types or the unique administrative status of capital prefectures in China. Table C.2 summarizes the results and illustrated in Figure 1. To further examine station count patterns, I employed Generalized

	Full dataset		Exclude reference stations		Exclude capital prefectures	
	HC2 SE	WLS	HC2 SE	WLS	HC2 SE	WLS
Pollution Permits (log)	0.517	0.447	0.604	0.514	0.576	0.488
	(0.276)	(0.178)	(0.269)	(0.169)	(0.316)	(0.189)
Province fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Num. Obs.	333	333	333	333	302	302
R2	0.222	0.250	0.237	0.221	0.202	0.263
R2 Adj.	0.142	0.170	0.159	0.138	0.123	0.188

Table C.2: OLS Regression Results: Station Coverage Gap Analysis.

Additive Models (GAM), which can detect non-linear relationships without requiring pre-specified functional forms.[28] Using the raw count of monitoring stations in each prefecture as the dependent

[27] It is described in Table B.1.

[28] Hastie and Tibshirani (2017).

	Full dataset			Exclude reference stations			Exclude capital pref.		
	Mod 1	Mod 2	Mod 3	Mod 1	Mod 2	Mod 3	Mod 1	Mod 2	Mod 3
edf	3.583	7.829	7.469	3.268	6.693	7.766	4.086	8.650	8.658
Ref.df	4.459	8.638	8.417	4.085	7.804	8.606	4.992	8.963	8.965
F stat.	78.170	8.445	6.529	93.079	8.601	6.986	51.586	12.171	7.21
p-val	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Control		✓	✓		✓	✓		✓	✓
FEs			✓			✓			✓

Table C.3: Generalized Additive Model Results: Relationship between Pollution Proxies and Station Counts

variable, I first controlled for factors specified in technical guidelines (population and urban built-up area). I then added pollution levels as a smooth term to test for additional influences on station placement. The effective degrees of freedom (edf) of this pollution term quantifies the complexity of any relationship beyond technical factors: an edf of 1 would indicate a simple linear relationship, while higher values reveal increasingly complex, non-linear patterns.[29] I test multiple model specifications as robustness checks, with the following base model:

$$g(\text{Station Count}_i) = \alpha + s(\text{pollution}_i) + \mathbf{X}_i\boldsymbol{\delta} + \lambda_j + \epsilon_i \tag{2}$$

where g is a link function and s is a smooth function. The dependent variable Station Count$_i$ is the logarithm of the raw station count in each prefecture. The parametric component $\mathbf{X}_i\boldsymbol{\delta}$ includes population and built-up area. Some specifications also include province fixed effects j to account for provincial variation in implementation.

Table C.3 presents the results from different model specifications. The estimated edf of the pollution term ranges from 3.583 to 8.658 across specifications, with all smooth terms being statistically significant. These high edf values indicate that the relationship between pollution levels and station numbers is both complex and non-linear, even after controlling for technical guideline factors.

C.2 Study 3: Station Shutdowns During Pollution Spikes

I use the synthetic difference-in-differences estimator (SDID) to identify the causal effect of the extreme pollution event on monitoring station operation. SDID is an estimation strategy that combines difference-in-differences (DID) and synthetic control methods. The method re-weighs the control units so that the pre-exposure trends are approximately parallel to the treated, then applies the DID analysis to the re-weighted panel, focusing on a subset of pre-exposure time periods with non-

[29] Zuur et al. (2009).

zero weights. In essence, "The use of weights in the SDID estimator effectively makes the two-way effect regression 'local,' in that it emphasizes (puts more weight on) units that are on average similar in terms of their past to the target (treated) units, and it emphasizes periods that are on average similar to the target (treated) periods."[30]

The SDID estimator offers several advantages over traditional DID and synthetic control methods. By re-weighting the control units, SDID reduces the reliance on the parallel trend assumption, which is a critical requirement for the validity of DID estimates. Additionally, unlike the synthetic control method, SDID is invariant to additive unit-level shifts, making it more robust to certain types of unobserved confounding factors. Simulation studies have demonstrated that SDID outperforms other approaches in terms of robustness and coverage rates, providing more reliable estimates of causal effects. The average causal effect of exposure τ is:

$$\left(\hat{\tau}^{\text{sdid}}, \hat{\mu}, \hat{\alpha}, \hat{\beta}\right) = \underset{\tau,\mu,\alpha,\beta}{\arg\min} \left\{ \sum_{i=1}^{N} \sum_{t=1}^{T} \left(Y_{it} - \mu - \alpha_i - \beta_t - W_{it}\tau\right)^2 \hat{\omega}_i^{\text{sdid}}\, \hat{\lambda}_t^{\text{sdid}} \right\} \tag{3}$$

Where N denotes units and T denotes time periods. $W_{it} \in \{0,1\}$ is a binary treatment indicator. $\hat{\omega}_i^{\text{sdid}}$ are the unit weights that align pre-exposure trends in the outcome of control units to those of the treated units: $\sum_{i=1}^{N_{co}} \hat{\omega}_i^{\text{sdid}} Y_{it} \approx N_{tr}^{-1} \sum_{i=N_{co}+1}^{N} Y_{it}$ for all pre-exposure time periods, where the first N_{co} (253) units are the controls, and the last N_{tr} (83) are the treated. $\hat{\lambda}_i^{\text{sdid}}$ are the time weights that balance pre-exposure time periods with the postexposure ones.

Figure C.5 presents the unit-specific weights assigned to control prefectures and their adjusted outcomes. Each panel displays results for a different monitored pollutant, where vertical grids represent control prefectures (sorted by administrative codes) and the dark horizontal line indicates the SDID estimate. Two key patterns emerge: the weights are broadly distributed across control prefectures rather than concentrated on a few units, demonstrating the SDID approach's effectiveness in mitigating outlier influence, and the weighted values cluster tightly around the estimate lines, indicating tighter fit of the control unit contributors to the estimate line. These patterns confirm that the results are not driven by extreme values or anomalous patterns in any subset of control prefectures.

[30] Arkhangelsky et al. (2021).

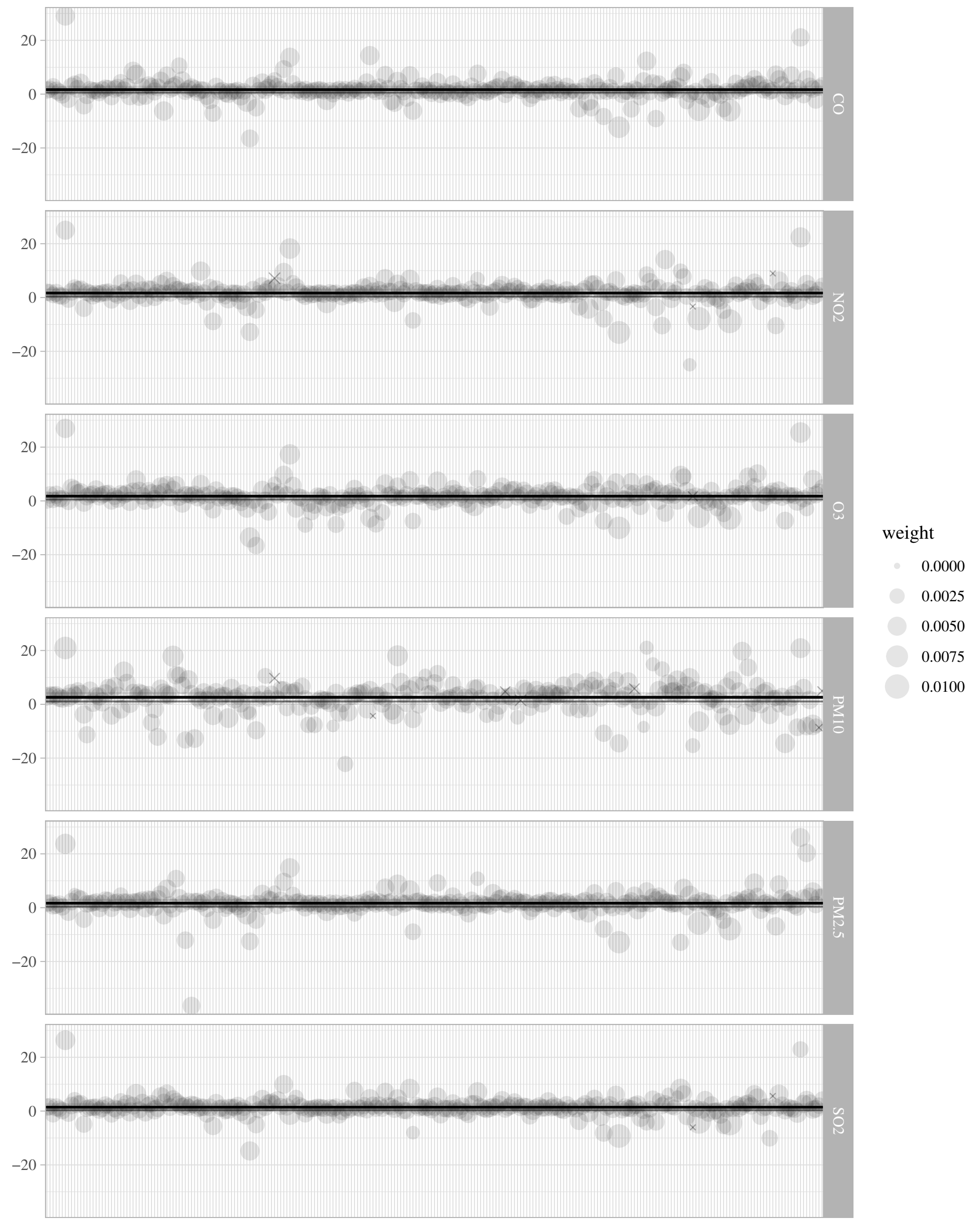


Figure C.5: SDID Unit Plots: The prefecture-by-prefecture adjusted difference-in-differences outcome, with the unit weights $\hat{\omega}_i$ indicated by dot size. The dark horizontal line indicates the estimated effect size. Observations with zero weight are indicated by $\times$ symbols.

References

Arkhangelsky, Dmitry, Susan Athey, David A Hirshberg, Guido W Imbens and Stefan Wager. 2021. "Synthetic Difference-in-Differences." *American Economic Review* 111(12):4088–4118.

Baidu Library. 2006. "2006 List of Ambient Air Monitoring Stations in 113 Key Cities Across the Country.".

Baidu Library. 2008. "2008 Ambient Air Monitoring Sites in Cities Above Prefectural Level.".

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):815–850.

Cao, Jun. 2015. "How Much Change Does Nationalizing the Monitoring Stations Bring?—Ten Questions about Nationalizing the Ecological and Environmental Quality Monitoring." *Environment Economy* .

CCTV.NET. 2021. "Ministry of Ecology and Environment: Over Three Million Fixed Pollution Sources Nationwide Are Included in the Pollutant Discharge Portal.".

General Office of Ministry of Ecology and Environment. 2018. Regarding the Issuance of the "Technical Regulations for Urban Environmental Air Quality Ranking" Notice [Guanyu Yinfa "Chengshi Huanjing Kongqi Zhiliang Paiming Jishu Guiding" De Tongzhi]. Technical report.

General office of the Ministry of Environmental Protection. 2012. Regarding the Request to Confirm the Assessment Points for Environmental Quality in the Comprehensive Urban Environmental Remediation during the "Twelfth Five-Year Plan" [Guanyu Qing Queding "Shierwu" Chengshi Huanjing Zonghe Zhengzhi Dingliang Kaohe Huanjing Zhiliang Kaohe Dianwei De Han]. Technical report.

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.

Guangdong Department of Ecology and Environment. 2020. "2020 Guangdong Province Ecological Environment Monitoring Plan (Public Version).".

Hastie, Trevor J and Robert J Tibshirani. 2017. *Generalized Additive Models*. Routledge.

Hsu, Angel, Alex de Sherbinin and Han Shi. 2012. "Seeking Truth from Facts: The Challenge of Environmental Indicator Development in China." *Environmental Development* 3:39–51.

Lifeweek. 2014. "Environmental Protection Requires Both Tackling and Fighting a Protracted Battle - An Exclusive Interview with Wu Xiaoqing, Vice Minister of Environmental Protection.".

Ministry of Environmental Protection. 2012. Notice on Printing and Distributing the Plan for the Establishment of the National Surface Water and Ambient Air Monitoring Network (Cities Above the Prefectural Level). Technical report.

Ministry of Environmental Protection. 2013. "China's Technical Regulation for Selection of Ambient Air Quality Monitoring Stations [Huanjing Kongqi Zhiliang Jiance Dianwei Bushe Jishu Guifan] 2013 (HJ 664-2013).".

Ministry of Environmental Protection. 2016. "2015 China Environmental State Bulletin.".

National Energy Administration. 2020. "All Point Source Pollution in Our Country Will Achieve "One Certificate" Management This Year.".

State Council. 2011. "Notice from the State Council on the Issuance of the "12th Five-Year Plan" for National Environmental Protection (Guowuyuan Guanyu Yinfa Guojia Huanjing Baohu "Shi Er Wu" Guihua De Tongzhi)." https://www.gov.cn/zwgk/2011-12/20/content_2024895.htm. Accessed: 2023-8-22.

State Environmental Protection Administration. 2007. "Ambient Air Quality Monitoring Standards (Trial).".

The General Office of the Ministry of Environmental Protection. 2014. "The Third Phase Monitoring Implementation Plan of the New Air Quality Standard.".

The General Office of the Ministry of Environmental Protection. 2017. "Notification on the Recent Situation of Some City Environmental Air Quality Automatic Monitoring Stations Affected by Sprinkler Interference [Guan Yu Jin Qi Bu Fen Cheng Shi Huan Jing Kong Qi Zhi Liang Zi Dong Jian Ce Zhan Dian Shou Dao Pen Lin Gan Rao You Guan Qing Kuang De Tong Bao]." https://www.mee.gov.cn/gkml/hbb/bgth/201801/t20180114_429693.htm. Accessed: 2023-11-15.

Zhang, Jin, Han Xiao, Qingyue He, Jie Peng, Ding Li and Yuan Liu. 2024. "When to Issue the Alert of Air Pollution in Chinese Cities? Evidence on the Threshold Effect of Heavy Air Pollution from Chengdu." *Environmental Impact Assessment Review* 105:107371.

Zhao, Hanping, Fangping Wang, Chence Niu, Han Wang and Xiaoxue Zhang. 2018. "Red Warning for Air Pollution in China: Exploring Residents' Perceptions of the First Two Red Warnings in Beijing." *Environmental research* 161:540–545.

Zuur, Alain F, Elena N Ieno, Neil Walker, Anatoly A Saveliev and Graham M Smith. 2009. *Mixed Effects Models and Extensions in Ecology with R*. Springer New York.