

Pollution in the Administrative Calculus: Evidence from Land Allocation in China

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Abstract

Understanding when and how environmental objectives enter government decision-making is central to the design of effective regulation in decentralized systems. This paper studies how pollution becomes decision-relevant for local governments by modeling urban land supply choices through a revealed-preference framework. Using the staggered strengthening of environmental targets associated with China's national air-quality governance reforms since 2012, we structurally recover the parameters governing local governments' trade-offs between fiscal revenue and environmental quality. We find a sharp reweighting of policy objectives once environmental considerations become institutionally salient. On average, local governments are willing to forgo 6.37% of expected fiscal revenue from a land parcel to avoid a 1% increase in local PM_{2.5} concentrations. This implied valuation substantially exceeds existing estimates of residents' private willingness to pay for cleaner air, disciplining the role of administrative decision-making relative to bottom-up market demand. Importantly, the incorporation of pollution into the administrative calculus is highly uneven across space. We document pronounced strategic responses in land allocation: the implied valuation of pollution is extremely high within 3 kilometers of monitoring stations but declines rapidly and becomes negligible beyond 6 kilometers. These spatial patterns suggest that while stronger top-down environmental targets can effectively alter local government behavior, they may also distort land allocation and generate new forms of spatial environmental inequality.

Keywords: Environmental regulation, local government incentives, air pollution, land use

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1 Introduction

Environmental regulation in decentralized systems ultimately depends on how governments trade off competing policy objectives. While environmental quality is widely recognized as socially valuable, local governments often face strong fiscal pressures and development incentives that pull policy in the opposite direction. Understanding when environmental considerations enter government decision-making, where they matter most, and how they are weighed against revenue-generating objectives is therefore central to the design and effectiveness of environmental regulation.

A large and growing literature studies how regulatory institutions, monitoring technologies, and top-down mandates affect pollution outcomes, documenting substantial reductions in measured pollution following stricter oversight and a variety of strategic responses by regulated agents and local governments (e.g., Zou, 2021; Greenstone et al., 2022; Axbard and Deng, 2024; Kong and Liu, 2024). However, this literature largely infers government behavior from observed outcomes, treating the underlying decision rule of enforcers as a black box. As a result, we have limited evidence on governments' objective functions: how much fiscal revenue they are willing to sacrifice for environmental improvements, how these trade-offs change when environmental objectives become institutionally salient, and how they vary across space and jurisdictions.

This paper addresses this gap by recovering the trade-offs governing local governments' policy choices from observed behavior. We study urban land supply, a core policy instrument through which local governments shape economic development and generate fiscal revenue. For each land parcel, local governments choose whether to allocate land to industrial or residential use, trading off long-term fiscal and growth considerations against environmental impacts and land-market valuations. We model these land-use decisions as a revealed-preference problem, which allows us to structurally recover the parameters governing local governments' trade-offs between fiscal revenue and environmental quality. Crucially, because land-use types are determined unilaterally by governments prior to market auctions, this setting enables us to analyze governments' expected payoffs without the confounding influence of bargaining with developers.

To operationalize this framework, we exploit an institutional change that altered the incentive environment faced by local governments. Beginning in the early 2010s, China strengthened the role of environmental performance in the evaluation of local officials through a series of national air-quality governance reforms. Central to these reforms was the establishment of a nationwide system for collecting and verifying pollution data, which reduced local discretion over environmental reporting and increased the salience of pollution outcomes in administrative assessments (Barwick et al., 2024; Yang et al., 2024). Together, these changes marked a regime shift in which environmental quality became a binding policy objective for local governments rather than a largely symbolic mandate.

We leverage the staggered rollout of the monitoring reforms starting in late 2012 to study how local governments' revealed trade-offs between fiscal revenue and environmental quality changed once environmental objectives entered the administrative calculus. Prior to this shift, environmental constraints were weakly enforced, and land supply decisions were largely driven by fiscal considerations. We use this pre-reform period to estimate a counterfactual benchmark in which local governments

allocate land to maximize expected fiscal returns in the absence of environmental targets.

Following the monitoring reform, the strengthened environmental regime altered local governments' incentives through several distinct economic and political channels. First, improved transparency and verification of pollution outcomes increased the sensitivity of residential land values to local air quality, directly affecting the expected fiscal returns from residential land supply. Second, tighter environmental regulation reduced the profitability and output of polluting industrial activities, lowering the expected future tax revenues associated with industrial land allocation. Third—and most critically—the incorporation of environmental performance into administrative evaluations compelled local governments to internalize the political costs of pollution, effectively assigning a shadow price to environmental degradation within their decision-making process. Our empirical strategy is designed to disentangle these channels and to recover the shadow price of pollution implied by observed land-use choices.

Our empirical strategy proceeds in steps. First, to capture the residential land price channel, we estimate how the pollution elasticity of prices changed after the monitoring rollout. Leveraging the staggered implementation of the network and using thermal inversions as an instrumental variable for pollution, we find that transparency significantly disciplined the market: the sensitivity of residential land prices to pollution intensified, with the elasticity coefficient becoming more negative by 0.32 in the first wave of monitored cities. Combining this parameter with the estimated pre-monitoring counterfactual fiscal revenue function, we project local governments' expected fiscal revenue differentials between the two land use types for each parcel transacted following the monitoring.

Next, to quantify the pollution costs, we estimate the counterfactual pollution caused by industrial land supply. By matching industrial parcels with comparable non-transacted grid cells, we trace the *ex-post* pollution trajectory. We find that supplying an industrial parcel leads to a persistent increase in local $\text{PM}_{2.5}$ concentrations, on average peaking at 3% three years post-transaction. Combining these estimates, we construct the expected pollution differential between the two land use types.

With the expected fiscal and pollution components identified, we recover the parameters of the local governments' objective function. Our structural estimates reveal a profound shift in governance priorities. On average, local governments are willing to forego 6.37% of the expected fiscal revenue from a land parcel to avoid a 1% increase in local $\text{PM}_{2.5}$ concentrations. This implies a remarkably high implicit shadow price of pollution: specifically, approximately 832 USD per person (or, more conservatively, 42.41 USD, when assuming substantial externalities) for a $1 \mu\text{g}/\text{m}^3$ reduction. Crucially, this political valuation substantially exceeds the residents' private willingness-to-pay for clean air estimated in the literature. This valuation gap provides quantitative evidence that China's environmental turnaround is driven primarily by top-down political pressure rather than bottom-up market demand.

However, this high-powered political accountability comes with unintended consequences. Driven by the intense pressure to meet monitoring targets, local governments engage in strategic spatial gaming. We document a “ring effect”: the shadow price of pollution, as inferred from land use decisions, is exceptionally high for parcels situated within a 3-kilometer radius of a monitoring station, yet it rapidly diminishes with increasing distance, becoming statistically insignificant beyond

6 kilometers. Thus, we identify local governments' land-based spatial strategic behavior, indicating that enforcement is predominantly concentrated in areas under direct central scrutiny. Furthermore, this strategic behavior is heterogeneous: it is most pronounced among city leaders with stronger promotion incentives or a historical emphasis on environmental protection.

Our study primarily contributes to three strands of the literature. First, we contribute to the political economy literature on environmental governance in decentralized systems (Esty, 1996; Oates and Portney, 2003; Jia, 2025). While existing studies have extensively documented the pollution-reducing effects of top-down mandates and monitoring technologies (Zou, 2021; Greenstone et al., 2022; Axbard and Deng, 2024; Kong and Liu, 2024), they primarily focus on environmental outcomes without quantitatively recovering the incentive parameters driving local enforcement. Consequently, the literature lacks a metric to directly compare the magnitude of political incentives against economic or social benefits. We bridge this gap by structurally estimating the shadow price of pollution in the utility function of Chinese local officials. Crucially, we benchmark these political estimates against the private willingness-to-pay for clean air established in the literature (Bayer et al., 2009; Greenstone and Jack, 2015; Freeman et al., 2019; Ito and Zhang, 2020; Nishitateno and Burke, 2021). Our results reveal that political pressure generates a valuation of clean air that far exceeds the market valuation. This highlights that China's rapid environmental turnaround is driven primarily by the strength of hierarchical accountability rather than responsive, bottom-up demand.

Second, we add to the literature on local governments' strategic behaviors in response to political pressure (Ghanem and Zhang, 2014; Kahn et al., 2015; Cai et al., 2016; Zou, 2021; Cao et al., 2023; Hong and Huang, 2025), especially when central monitoring lacks complete spatial coverage (He et al., 2020; Xie and Yuan, 2023; Cui et al., 2024; Yang et al., 2024). Previous studies, most notably Yang et al. (2024), have documented spatially localized enforcement, showing that pollution reductions are concentrated near monitoring stations. However, relying solely on pollution outcomes conflates the government's enforcement effort with pollution dispersion and physical externalities. We advance this line of inquiry by structurally recovering the spatially heterogeneous utility function itself. This allows us to isolate the government's intrinsic political valuation of clean air. We find an extremely sharp decay in political willingness—vanishing rapidly beyond 6 kilometers from monitors—which presents a more precise characterization of the “window dressing” behavior than outcome-based measures. Our results reinforce the limits of point-based monitoring: technology solves the data manipulation problem but merely shifts the principal–agent conflict to the spatial allocation of enforcement effort.

Third, we speak to the large body of literature on China's land zoning and urban development (Lichtenberg and Ding, 2009; Tao et al., 2010; Lu and Wang, 2020; Liu et al., 2022; Lu et al., 2024). Urban land supply in China is typically viewed primarily as a fiscal instrument to maximize revenue or an industrial policy tool to attract investment (Shu et al., 2018; Wang et al., 2020), with recent work confirming that even industrial land serves as a crucial long-term tax base (He et al., 2022). However, only a few studies provide suggestive evidence that environmental constraints act as an *ex-ante* determinant of land supply decisions (Xie and Yuan, 2023; Yang et al., 2024). We advance this framework by quantitatively integrating environmental incentives directly into the land

supply model. We demonstrate that under the strict monitoring regime, land zoning has evolved from a purely growth-oriented instrument into a multi-dimensional tool that balances fiscal needs with environmental mandates. Crucially, we show that this evolution has distributional consequences: due to the incomplete spatial coverage of monitoring, this new zoning logic is reshaping the landscape of environmental inequality across urban China.

The remainder of this paper is structured as follows. Section 2 provides the relevant institutional background. Section 3 develops a theoretical framework for recovering local governments' preference parameters based on their observed land use decisions, concluding by outlining a four-step roadmap for our empirical analysis. Section 4 summarizes our primary datasets. Section 5 implements the first step of this roadmap, estimating the causal effects of national monitoring on the elasticity of residential land prices with respect to pollution. Section 6 proceeds to the second and third steps, focusing on estimating local governments' expected fiscal revenues and the induced pollution associated with land supply. Section 7 synthesizes these estimates to recover local governments' utility function and explores heterogeneity. Finally, Section 8 concludes the study.

2 Institutional background

This section outlines the institutional background relevant to our research. Given that several studies have leveraged the national atmospheric monitoring network for empirical investigations (e.g., Xie and Yuan, 2023; Barwick et al., 2024; Yang et al., 2024), we provide an overview of its underlying motivation, implementation, and subsequent consequences, tailored to establish the necessary context for our study. We then proceed to discuss China's urban construction land transaction system, emphasizing the pivotal role of prefecture-level governments in determining land zoning and delineating the distinctions among various land types.

2.1 National air quality governance reforms and monitoring network

In recent decades, China has experienced unprecedented economic growth, which has, however, come at a significant environmental cost (Yi et al., 2007; Zhang and Wang, 2011; Rohde and Muller, 2015). To address the pervasive issue of air pollution, the China's central government established its inaugural national ambient air quality standard (NAAQS) in 1982, and has subsequently implemented progressively stringent enforcement mechanisms (Li and Wang, 2025). With the issuance of the Tenth Five-Year Plan in 2001, pollution reduction was elevated to a national strategic objective. Since 2005, the central government has reoriented its national priority from mere development to "scientific development," underscoring the important role of emission reduction in the performance evaluation of local governments. However, despite the strategic importance accorded to environmental protection, China did not achieve the desired outcomes in pollution regulation during the 2000s.¹

¹As depicted in Appendix Figure E.1, the average $PM_{2.5}$ concentration did not decline but instead exhibited an increasing trend throughout the 2000s. This trend was not reversed until 2014. Moreover, during this period, severe air pollution was consistently observed during the autumn and winter months.

These suboptimal outcomes were closely related to China's decentralized governance structure, which is typically characterized as "political centralization with economic decentralization." Focusing on environmental regulation, the central government established environmental standards intended to be met through local government efforts and integrated these standards into local governments' performance assessments (Ghanem and Zhang, 2014). However, this system confronts two significant challenges. The most prominent one is that the environmental goal inherently contradicts the long-pursued objective of economic growth by local governments (Montinola et al., 1995; Qian and Weingast, 1997; Li and Zhou, 2005). Given the historical emphasis placed on economic growth over other socioeconomic goals, local governments have long acquiesced to the illegal production activities of polluting firms for economic gain. This phenomenon persisted even after the central government's increased emphasis on environmental protection, partially attributable to the second challenge: the weak monitoring and enforcement capabilities of the central government.² Specifically, prior to 2012, local governments were responsible for managing and operating monitors and collecting data for submission to central authorities, thereby creating significant scope for data manipulation. To meet the "blue-sky days" criteria, defined as an Air Pollution Index below 100, formulated by the central government, local governments tended to under-report local pollution levels (Ghanem and Zhang, 2014; Ghanem et al., 2020; Greenstone et al., 2022). Furthermore, they also frequently resorted to shutting down monitors during heavily polluted days and sabotaging monitoring equipment (Yang et al., 2024). As a result, local governments continued to have a weak incentive for environmental protection.

In 2012, China's central government revised the NAAQS, wherein PM_{2.5} concentration was incorporated into the national standard for the first time.³ This revised standard stipulates the limit values for the average concentrations of various pollutants, effective since 2016. Furthermore, it explicitly underscores that effective assessment relies on the accuracy, continuity, and completeness of monitoring data. To facilitate the achievement of these standards, China's central government has subsequently enacted a comprehensive and exceptionally rigorous suite of policies aimed at pollutant control, with a particular emphasis on particulate matter.⁴ These policies included signing Target Responsibility Agreements with each provincial government and stipulating detailed pollution reduction targets and environmental performance assessment metrics. Significantly, the central government mandated the establishment of a nationwide monitoring network, comprising automatic pollutant monitoring stations under direct central government authority, intended to cover all prefecture-level administrative regions by 2015. This monitoring network circumvents local gov-

²Another frequently cited cause is the absence of an effective interregional coordination system. In response to this deficiency, local governments often manipulated the spatial distribution of polluting firms through differentiated regulatory enforcement, thereby transferring pollution to other jurisdictions and leading to significant cross-boundary pollution (Cai et al., 2016; Cui et al., 2024).

³The official document of this new standard is available at <https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/dqhjbh/dqhjzlbz/201203/W020250407403788086276.pdf> (accessed December 2025).

⁴For instance, the "Action Plan for Air Pollution Prevention and Control," a programmatic policy document issued in 2013, explicitly states that "regional atmospheric environmental issues characterized by particulate matter (PM₁₀ and PM_{2.5}) are becoming increasingly prominent." This document further sets explicit targets for particulate matter control by 2017, mandating a reduction of over 10% in all prefecture-level administrative regions, a 25% decrease for the Beijing-Tianjin-Hebei Region, 20% for the Yangtze River Delta, and 15% for the Pearl River Delta. This policy document is available at https://www.gov.cn/zwgc/2013-09/12/content_2486773.htm (accessed December 2025).

ernment interference and addresses the critical issue of data manipulation, thereby inaugurating an unprecedented era of genuinely robust regulatory enforcement in China.

The implementation of this national monitoring network unfolded in three waves between 2012 and 2014, as illustrated in Figure 1. Notably, the policy design significantly mitigates concerns regarding selection bias stemming from local governments' prior interventions and substantially alleviates measurement errors. First, cities were allocated to these waves largely based on pre-existing administrative hierarchies and designated statuses, which were established well in advance of the monitoring program's inception. Furthermore, the placement of individual monitors was determined by geographical, meteorological, and socioeconomic factors, operating independently of local government influence, aiming to accurately represent the average air quality within the urban areas of each city.⁵ Moreover, the number of stations assigned to each city was contingent upon its population size and land area. However, given that monitoring stations are inherently unable to provide complete spatial coverage of an entire city, this still permits local governments to engage in spatially strategic behaviors (Yang et al., 2024). Specifically, and forming the central focus of our study, local governments may strategically adjust their land supply decisions in areas proximate to these monitors to manage reported pollution levels while concurrently minimizing any adverse impact on economic growth. We aim to elucidate this specific channel in the subsequent analysis.

Concurrently, this monitoring network also profoundly transformed public awareness regarding environmental pollution. Unlike prior data, which were often characterized by incompleteness and limited transparency, this network provides comprehensive, real-time, and high-quality air pollution information with public accessibility. This increased transparency has significantly influenced residents' pollution-avoidance behaviors (Wang and Zhang, 2023; Barwick et al., 2024) and patterns of residential spatial sorting (Rao, 2022). These shifts, in turn, can induce a demand-side shock on the land market and subsequently impact local governments' land supply decisions.

2.2 Urban construction land transaction system

China is characterized by a distinct dual land tenure system, wherein urban land is state-owned, while rural land is collectively owned by farmers. In urban areas, an institutional framework was implemented to enhance land-use efficiency without altering the fundamental ownership structure. This was achieved through a leasing system that separates land use rights from land ownership, all regulated by a hierarchical land quota system (Zhu, 2004). On one hand, local governments are authorized to lease urban land, commonly referred as "construction land," to market entities. Furthermore, they are often empowered to expropriate underutilized land and agricultural land from the urban sector, contingent upon the provision of appropriate compensation, thereby expanding the pool of land designated for development. On the other hand, to safeguard agricultural land and control urban expansion, the central government formulates the nation's long-term land development plan, which stipulates the maximum allowable area for newly developed urban construction land (Wang

⁵We present the location of each monitoring station in Appendix Figure A.2. As evidenced by Yang et al. (2024), the absolute percentage difference between the population-weighted average pollution in monitored areas and that of the entire city was less than 15% in most cities in 2008, well before the national rollout.

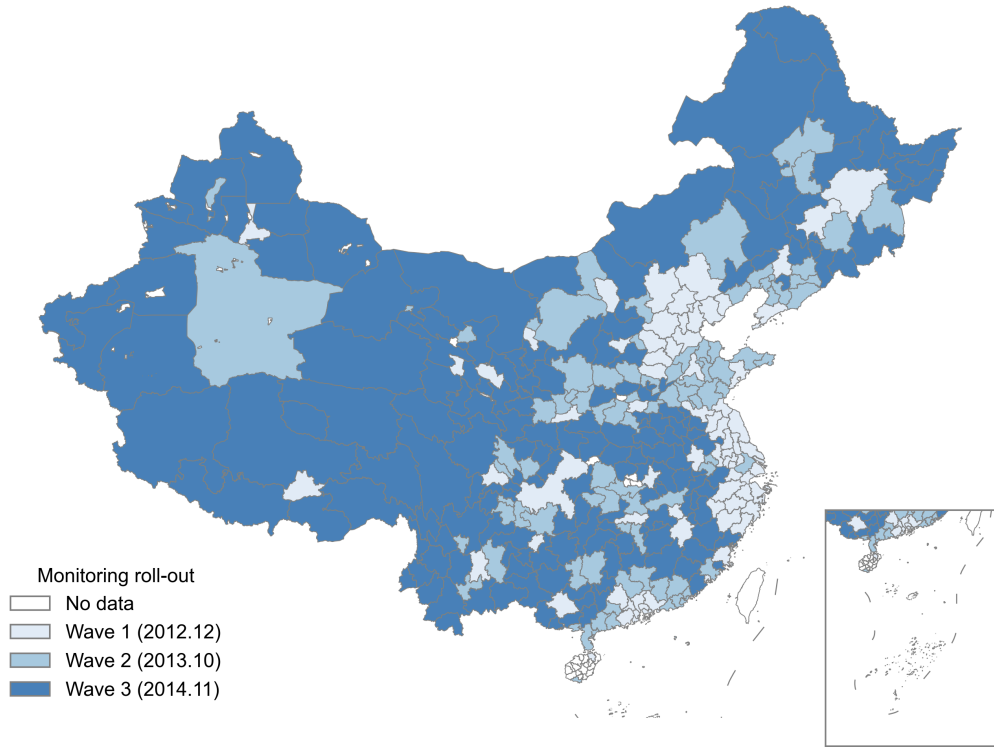


Figure 1: rollout of China’s national atmospheric monitoring network

Notes: This figure illustrates the three-wave implementation of China’s national atmospheric monitoring network. The complete list of city names is provided in Appendix Table E.1. Several county-level cities that could not be unambiguously consolidated with a specific prefecture-level administrative region are excluded from our study (represented as “No data” in this figure). The deadline month for cities in each wave to complete the installation of automatic monitoring stations is also indicated in the legend, according to official policy documents. These documents are accessible at <https://www.mee.gov.cn/gkml/hbb/bgt/201205/W020120524383009550407.pdf> for Wave 1, <https://www.mee.gov.cn/gkml/hbb/bgt/201303/W020130328510299736496.pdf> for Wave 2, and <https://www.mee.gov.cn/gkml/hbb/bwj/201405/W020140509376439653789.pdf> for Wave 3 (all accessed December 2025).

et al., 2020).⁶ During our study period (2010–2018), the central government issued annual land use quotas to each province to facilitate the achievement of this long-term plan. Provincial governments were subsequently required to formulate their own annual land development plans and allocate these land quotas to their subordinate prefecture-level administrative regions. In response, prefecture-level governments and their subordinate authorities are responsible for specifying zoning plans and planning areas for each land use type.⁷ Consequently, while the total area of urban construction land is centrally restricted, prefecture-level governments retain substantial discretion over zoning and land use within their jurisdictions (He et al., 2022).

According to the *Current Land Use Classification*, issued by the National Standardization Administration, the land use for construction land parcels is classified into eight types. Among these, the three types with the highest transaction volumes are residential, industrial, and commercial land, which account for 51.07%, 27.21%, and 18.8% of the total transaction records in our dataset, respectively.⁸ The remaining types typically encompass land designated for public facilities, such as transportation land and public administration and service land, and collectively represent a very minor proportion of the total. Consistent with prevalent methodologies in the existing literature, we consolidate residential and commercial land into a single type, henceforth termed “residential land” for simplicity. This consolidation is due to their similar contributions to local fiscal revenue and their relatively low direct pollution profiles, thereby forming a distinct counterpart to industrial land.

In recent decades, revenues generated from urban land transactions constitute a significant proportion of total local fiscal revenues (Liu, 2018; Liu et al., 2022; Lu et al., 2022), though contributions vary across land types. As depicted in Appendix Figure E.2, the average transaction price for residential land is notably high and exhibited a gradual increase from approximately 1,500 CNY/m² in 2010 to roughly 4,000 CNY/m² in 2018, with prices being considerably higher in larger cities. Since there is no residential property tax in China, residential land primarily functions as a source of *ex-ante*, lump-sum fiscal income.⁹ Consequently, local governments typically leverage competitive, market-based allocation mechanisms, such as auctions, to maximize immediate returns.¹⁰

Conversely, the average unit price of industrial land has remained consistently low (approximately 220 CNY/m²) and stable throughout the period, with the price disparity between larger and

⁶For instance, the primary policy document guiding land development from 2010 to 2018 was *The National Outline for Overall Land Use Planning (2006–2020)*, available at http://www.npc.gov.cn/zgrdw/npc/xinwen/szyw/zyw/j/2008-10/24/content_1454511.htm (accessed December 2025). This document established total area controls for urban construction land for each province by 2010 and 2020.

⁷For example, in the 2011 land use plan of Guangxi Zhuang Autonomous Region (available at <https://dnr.gxzf.gov.cn/zfxxgk/fdzdgknr/zcfg/btgdgkwj/t16391153.shtml>), the Guangxi provincial government stipulated the total area of newly developed urban construction land for each city. Within 2011 prefecture-level plans of Guangxi, such as Nanning’s plan (available at https://zrzyj.nanning.gov.cn/zwgk_57/xxgk/tdgl/tdly/t2591669.html), the areas for different land use types are meticulously planned.

⁸In terms of the total area of land supplied, residential, industrial, and commercial land represent 33.11%, 48.2%, and 14.34% of the total, respectively. Industrial land holds the largest total area, primarily because the individual land parcels involved in industrial transactions are typically larger.

⁹Specifically, for commercial land, revenue streams from establishments such as shops within a built shopping center also provide long-term tax revenues for local governments. However, given their fragmented nature and position at the end of the production chain, these individual tax revenues are substantially more limited compared to those generated by industrial firms.

¹⁰This practice was further solidified with a central government’s legislation in 2002, which stipulated that all profit-oriented land—such as land for commercial activities and commodity housing—must be transacted through auctions.

smaller cities remaining relatively modest. Considering the costs associated with land expropriation from the rural sector and infrastructure development prior to sale, this price may even be insufficient to cover these expenditures in certain instances. Moreover, land acquisition costs for industrial projects are often amortizable and tax-deductible for corporate income tax purposes. Therefore, the low price of industrial land is sometimes characterized as “zero price” or even “negative price” (Lu and Wang, 2020). This disparity between industrial and residential land is typically attributed to a suboptimal equilibrium of the “race to the bottom” competition among local governments, aiming to attract investment, promote local economic development, and expand their tax bases (Tao et al., 2010). Consequently, industrial land functions as a strategic instrument for local governments to cultivate long-term, *ex-post* fiscal capacity, prioritizing future revenues over immediate income (He et al., 2022).

In summary, these institutional backgrounds present local governments with a fundamental trade-off. On one hand, supplying industrial land is crucial for long-term economic growth and tax base cultivation. On the other hand, supplying commercial and residential land generates substantial immediate fiscal revenue with a comparatively smaller environmental footprint. The establishment of the national air quality monitoring network fundamentally reshapes the calculus of this trade-off, thereby offering a unique opportunity to quantify the objective function of local governments and investigate their strategic responses to the network’s partial spatial coverage.

3 A theoretical framework of local governments’ land supply decision

In this section, we develop a discrete choice model to characterize local governments’ decisions regarding land type, specifically between industrial land (I) and residential land (R). This framework enables us to quantify the relative importance of environmental protection objectives versus fiscal revenue objectives for local governments following the establishment of the national monitoring network.

To reflect the weak environmental protection incentives stemming from lax central monitoring prior to the establishment of the monitoring network ($\bar{t}_{\text{monitor}}$), we suppose that local governments’ land supply decisions are primarily driven by expected fiscal revenues. This is formally represented by the following Cobb–Douglas utility function:

$$U_{n,i,j,t}^0 = \alpha^0 \ln V_{n,i,j,t}^0 + \varepsilon_{n,i,j,t}^0, \quad t < \bar{t}_{\text{monitor}}, \quad (1)$$

where $V_{n,i,j,t}^0$ denotes the expected fiscal revenue for local government n if unit land parcel i is supplied as type $j \in \{I, R\}$ at time t , and $\varepsilon_{n,i,j,t}^0$ represents the unobserved utility component, drawn from a probability distribution $F_{\varepsilon^0}(x)$ with mean μ_{ε^0} and standard deviation σ_{ε^0} . Parameter α^0 reflects the pre-monitoring relative importance of the expected fiscal revenue component.¹¹

¹¹Let the underlying utility function be

$$\tilde{U}_{n,i,j,t}^0 = \left(V_{n,i,j,t}^0 \right)^{\bar{\alpha}^0} \left(u_{n,i,j,t}^0 \right)^{\bar{\varepsilon}^0}, \quad t < \bar{t}_{\text{monitor}},$$

where the mean and standard deviation of $\ln u_{n,i,j,t}^0$ are $\mu_{\ln u^0}$ and $\sigma_{\ln u^0}$, respectively. Applying a positive monotonic

It is important to note that the determination of each parcel's type by local governments precedes the public announcement of its supply. Consequently, at the time of this determination, local governments can only plausibly forecast expected revenues based on a combination of locational attributes (e.g., existing pollution levels and distance to the city center) and the characteristics of the parcel itself. For instance, a residential land parcel situated in an area with a higher pollution level would likely yield systematically lower prices for houses constructed thereon, which would, in turn, influence the parcel's transaction price.¹² Formally, this expected revenue per unit parcel is modeled as a linear function of several key factors:

$$\ln V_{n,i,j,t}^0 = \mu^j + \gamma^j \ln Pollution_{i,t} + \lambda^j \ln Distance_i^{\text{pop}} + X_i' \beta^j + \delta_{c(i)}^j + \zeta_{q(t)}^j, \quad j \in \{I, R\}, \quad (2)$$

where $Pollution_{i,t}$ and $Distance_i^{\text{pop}}$ represent the pollution level and the distance to the city's population center, respectively, associated with the location of parcel i , X_i is a vector of parcel-specific characteristics, encompassing its rank, transaction mechanism, and source, and $\delta_{c(i)}^j$ and $\zeta_{q(t)}^j$ denote city fixed effects and quarter fixed effects, respectively. As discussed in Section 2.2, fiscal revenues derived from selling residential land are primarily direct transaction income; thus, $\ln V_{n,i,R,t}^0$ represents local governments' expected transaction price. Assuming that local governments form this expectation by learning from historical patterns, we can identify γ^R based on land transaction data. Conversely, $\ln V_{n,i,I,t}^0$ reflects the expected long-term taxes and, when considered more broadly, potential political benefits stemming from industrial growth, which are not directly observable.

For each parcel i , local government n selects the land-use type that maximizes its utility. The probability of parcel i being transacted as industrial land, denoted $P_{n,i,I,t}^0$, is thus given by

$$\begin{aligned} P_{n,i,I,t}^0 &= \Pr \{U_{n,i,I,t}^0 \geq U_{n,i,R,t}^0\} \\ &= \Pr \left\{ \alpha^0 (\mu^I - \mu^R) + \alpha^0 (\gamma^I - \gamma^R) \ln Pollution_{i,t} + \alpha^0 (\lambda^I - \lambda^R) \ln Distance_i^{\text{pop}} \right. \\ &\quad \left. + X_i' \alpha^0 (\beta^I - \beta^R) + \alpha^0 (\delta_{c(i)}^I - \delta_{c(i)}^R) + \alpha^0 (\zeta_{q(t)}^I - \zeta_{q(t)}^R) \geq \varepsilon_{n,i,R,t}^0 - \varepsilon_{n,i,I,t}^0 \right\}. \end{aligned} \quad (3)$$

Under a specific distributional assumption for the difference in the unobserved term, the products of the preference parameter α^0 and the coefficient differences for each attribute across the two land-use types can be identified based on observed choices.

The establishment of the national monitoring network fundamentally alters the incentive structure transformation yields an equivalent utility function that preserves the underlying preference relationship:

$$U_{n,i,j,t}^0 = \frac{\sigma_{\varepsilon^0}}{\sigma_{\ln u^0}} \left(\frac{1}{\tilde{\varepsilon}^0} \ln \tilde{U}_{n,i,j,t}^0 - \mu_{\ln u^0} \right) + \mu_{\varepsilon^0} = \frac{\tilde{\alpha}^0}{\tilde{\varepsilon}^0} \frac{\sigma_{\varepsilon^0}}{\sigma_{\ln u^0}} \ln V_{n,i,j,t}^0 + \frac{\sigma_{\varepsilon^0}}{\sigma_{\ln u^0}} \left(\ln u_{n,i,j,t}^0 - \mu_{\ln u^0} \right) + \mu_{\varepsilon^0}.$$

By defining $\alpha^0 \equiv (\tilde{\alpha}^0 / \tilde{\varepsilon}^0) (\sigma_{\varepsilon^0} / \sigma_{\ln u^0})$ and $\varepsilon_{n,i,j,t}^0 \equiv (\sigma_{\varepsilon^0} / \sigma_{\ln u^0}) (\ln u_{n,i,j,t}^0 - \mu_{\ln u^0}) + \mu_{\varepsilon^0}$, we obtain the utility specification presented in Equation (1). The parameter α^0 is therefore a composite term, encapsulating both the relative importance of the two utility components, $\tilde{\alpha}^0 / \tilde{\varepsilon}^0$, and a scaling factor designed to establish a specific standard deviation for $\varepsilon_{n,i,j,t}^0$, and it is the only preference parameter that can be identified from observed choices.

¹²It should be emphasized that this refers to the *ex-ante* pollution level of the location, rather than the *ex-post* pollution increases that may result from the subsequent land supply and development.

ture for local governments. Specifically, the utility function is then assumed as

$$U_{n,i,j,t}^1 = \alpha^1 \ln V_{n,i,j,t}^1 + \theta^1 \ln \left(\frac{Pollution'_{i,j,t}}{Pollution_{i,t}} \right) + \varepsilon_{n,i,j,t}^1, \quad t \geq \bar{t}_{\text{monitor}}, \quad (4)$$

where α^1 and θ^1 are post-monitoring preference parameters, and $Pollution'_{i,j,t}$ denotes the expected counterfactual pollution level solely resulting from the transaction of unit parcel i as type j .¹³ Analogous to the fiscal revenue function, the expected difference in pollution increases between industrial and residential land parcels is modeled as a linear function of a set of land attributes and fixed effects:

$$\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t} = M'_{i,t} \rho, \quad (5)$$

where $M_{i,t}$ is a vector of covariates comprising the distance to the city population center, parcel rank, transaction mechanism, land source, city fixed effects, and quarter fixed effects. The coefficient vector ρ is interpreted as the differential effect of these covariates on pollution increases between the two land types.

Concurrently, the monitoring network could also alter local governments' expected fiscal revenue derived from the sale of two land types. Heightened public awareness, fostered by more transparent pollution information, may lead to an increased price sensitivity of housing to pollution levels. As land transaction income primarily constitutes the fiscal revenue generated from residential land sales, this demand-side shock may subsequently propagate through the residential land market, potentially diminishing governments' expected revenues. To capture this effect, the revenue function for a unit parcel of residential land subsequent to monitoring is modeled as

$$\ln V_{n,i,R,t}^1 = \mu^R + (\gamma^R + \phi) \ln Pollution_{i,t} + \lambda^R \ln Distance_i^{\text{pop}} + X_i' \beta^R + \delta_{c(i)}^R + \zeta_{q(t)}^R, \quad (6)$$

where parameter ϕ quantifies the causal effect of monitoring on the elasticity of residential land price with respect to pollution.

In contrast, fiscal revenues from industrial land transactions are primarily derived from future taxes on production. Given that numerous studies have demonstrated that stringent environmental regulations can adversely affect the aggregate output of manufacturing firms (Berman and Bui, 2001; Greenstone, 2002; He et al., 2020), it is anticipated that the implementation of national monitoring may consequently diminish local governments' expected present value of future tax revenues. Assuming this effect results in a decrease of $\tau_{c(i)}$ on tax revenues, with heterogeneity permitted across

¹³Following the implementation of monitoring, suppose the underlying utility function becomes

$$\tilde{U}_{n,i,j,t}^1 = \left(V_{n,i,j,t}^1 \right)^{\tilde{\alpha}^1} \left(\frac{Pollution'_{i,j,t}}{Pollution_{i,t}} \right)^{\tilde{\theta}^1} \left(u_{n,i,j,t}^1 \right)^{\tilde{\xi}^1}, \quad t \geq \bar{t}_{\text{monitor}}.$$

By applying a positive monotonic transformation, consistent with that used in deriving Equation (1), we define parameters $\alpha^1 \equiv (\tilde{\alpha}^1 / \tilde{\xi}^1)(\sigma_{\varepsilon^1} / \sigma_{\ln u^1})$ and $\theta^1 \equiv (\tilde{\theta}^1 / \tilde{\xi}^1)(\sigma_{\varepsilon^1} / \sigma_{\ln u^1})$, which, similar to α^0 , captures the relative utility weight, but adjusted by a standard deviation factor. It is noteworthy that the ratio θ^1 / α^1 is precisely equal to $\tilde{\theta}^1 / \tilde{\alpha}^1$, thereby allowing us to directly quantify the relative importance between the environmental protection objective and the fiscal revenue objective of local governments.

cities, the revenue function for industrial land subsequent to monitoring is then given by

$$\ln V_{n,i,I,t}^1 = \ln(1 - \tau_{c(i)}) V_{n,i,I,t}^0 = \ln(1 - \tau_{c(i)}) + \ln V_{n,i,I,t}^0, \quad (7)$$

where the first term can be captured by the city fixed effects in the estimation.¹⁴

Combining Equations (6) and (7) yields the revenue difference between the two land types after national monitoring:

$$\begin{aligned} \ln V_{n,i,I,t}^1 - \ln V_{n,i,R,t}^1 &= \ln(1 - \tau_{c(i)}) + (\mu^I - \mu^R) + (\gamma^I - \gamma^R - \phi) \ln Pollution_{i,t} \\ &\quad + (\lambda^I - \lambda^R) \ln Distance_i^{\text{pop}} + X_i'(\beta^I - \beta^R) + (\delta_{c(i)}^I - \delta_{c(i)}^R) + (\zeta_{q(t)}^I - \zeta_{q(t)}^R). \end{aligned} \quad (8)$$

The probability of parcel i being supplied as industrial land after monitoring, denoted as $P_{n,i,I,t}^1$, is given by

$$\begin{aligned} P_{n,i,I,t}^1 &= \Pr \{U_{n,i,I,t}^1 \geq U_{n,i,R,t}^1\} \\ &= \Pr \left\{ \alpha^1 (\ln V_{n,i,I,t}^1 - \ln V_{n,i,R,t}^1) + \theta^1 (\ln Pollution_{i,I,t}' - \ln Pollution_{i,R,t}') \geq \varepsilon_{n,i,R,t}^1 - \varepsilon_{n,i,I,t}^1 \right\}. \end{aligned} \quad (9)$$

Upon estimating the difference in expected revenue and pollution increases between the two land types, we are able to identify α^1 , θ^1 , and most importantly, their ratio θ^1/α^1 . This ratio quantifies the relative importance of the environmental protection objective compared to the fiscal revenue objective for local governments and facilitates our investigation of further heterogeneity.

Guided by this theoretical framework, our subsequent empirical analysis proceeds in the following four steps:

1. Estimate the causal effects of the national monitoring network on the elasticity of residential land price with respect to pollution, ϕ , by employing variation sourced from the staggered rollout of the network.
2. Estimate the differences in the coefficients of the fiscal revenue functions between the two land types, including $\mu^I - \mu^R$, $\gamma^I - \gamma^R$, $\lambda^I - \lambda^R$, $\beta^I - \beta^R$, $\delta_{c(i)}^I - \delta_{c(i)}^R$, and $\zeta_{q(t)}^I - \zeta_{q(t)}^R$, based on local governments' pre-monitoring land type decisions. Combining Steps 1 and 2 yields the estimation for each parcel's post-monitoring revenue difference, $\ln V_{n,i,I,t}^1 - \ln V_{n,i,R,t}^1$. To ensure the applicability of these pre-monitoring estimates, we limit the estimation sample to transactions occurring one year preceding the monitoring period and use them solely to predict revenue differences for transactions in the subsequent year of monitoring.
3. Estimate the coefficient vector ρ based on post-transaction pollution levels observed in a matched sample. This sample comprises grid cells subjected to land transactions and non-transacted cells demonstrating comparable pre-transaction pollution levels. Subsequently,

¹⁴A related concern is that, as local governments may implement differential regulation enforcement based on the distance to monitors, this tax reduction effect can exhibit heterogeneity within a city. To alleviate this concern, we will later provide a ring analysis based on the distance to the nearest monitoring station. For each ring, the comparison is restricted to land parcels with similar distance and, consequently, similar enforcement strength; the fixed effects are thus sufficient to absorb the reduction effect.

predict the expected difference in pollution levels, $\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}$, for each parcel transacted in the subsequent year of monitoring.

4. With the estimates derived from Steps 2 and 3, determine parameters α^1 and θ^1 that maximize the likelihood function constructed based on Equation (9). Following this, a ring analysis is employed, and the political incentives of local governments are further incorporated to explore heterogeneity across space and leaders.

4 Data

To implement the aforementioned four-step estimation, we compile multiple datasets covering 337 cities in China.¹⁵ This section provides an overview of the primary data sources, with detailed processing procedures relegated to Appendix A.

Land transaction data.—Our land transaction dataset encompasses the complete set of land transactions in China, sourced from China Land Market (<https://landchina.com>). This website, managed by China’s Ministry of Natural Resources, serves as the official repository for all historical land transaction records dating back to 1989. For our analysis, we utilize transaction records spanning from 2010 to 2018, resulting in 1,071,842 observations after cleaning. Each record provides detailed information, including the transaction date, total price, parcel size, address, buyer’s name and industry, transaction mechanism (e.g., auctions, agreements, administrative allotments), and land parcel rank, etc. Comprehensive explanations for these attributes and the data cleaning process are provided in the Appendix. Figure A.1 illustrates the geographical distribution of the parcels incorporated into the subsequent analysis.

Monitoring station data.—This dataset is sourced from the Hong Kong University of Science and Technology Atmospheric and Environmental Database, which provides information including names, geographical coordinates, cities, open years of 1,499 monitoring stations opened during 2012 to 2014. After dropping 6 stations that can not be concisely matched to a specific prefecture-level administrative regions, 1,493 of them remain in our dataset in use. We provide their locations in a map in Appendix Figure A.2.

Satellite-based atmospheric pollution data.—We utilize satellite-derived $PM_{2.5}$ data from the Atmospheric Composition Analysis Group to measure location-specific air quality in China (Shen et al., 2024). Specifically, we employ their V6.GL.02.04 dataset, which offers monthly and annual $PM_{2.5}$ concentration estimates at a spatial resolution of up to $0.01^\circ \times 0.01^\circ$ cells. We use the monthly datasets to construct quarterly $PM_{2.5}$ concentrations for each grid cell. Subsequently, we identify the grid cell corresponding to each land parcel to merge the land transaction data with the pollution data. We also construct a cell-level pollution panel dataset based on their coarser dataset with a resolution of $0.1^\circ \times 0.1^\circ$ cells.

¹⁵China’s administrative structure is composed of 34 provincial-level regions, which include 4 direct-administered municipalities (provincial-level cities): Beijing, Tianjin, Shanghai, and Chongqing. Most of these are further subdivided into 333 prefecture-level administrative regions, comprising 293 prefecture-level cities, 7 prefectures, 30 autonomous prefectures, and 3 leagues. In our empirical analysis, the term “city” refers to either a direct-administered municipality or a prefecture-level administrative region.

Thermal inversion data.—To mitigate potential endogeneity in identification, we construct an instrumental variable for the pollution level based on thermal inversion, a meteorological phenomenon characterized by a layer of warmer air overlying a layer of cooler air near the surface. For this purpose, we utilize data from NASA’s MERRA-2 product M2I6NPANA, version 5.12.4. This dataset provides air temperatures every 6 hours across 42 pressure levels, ranging from 1,000 hPa (approximately 110 m) to 0.1 hPa (approximately 65,000 m), with a spatial resolution of $0.625^\circ \times 0.5^\circ$.

Demographic data.—We primarily utilize demographic data to determine each city’s population center. This data is sourced from the Gridded Population of the World (GPWv4) dataset, specifically Version 4.11, also provided by NASA. This dataset offers estimates of the population count per cell, based on the 2010 national census in China, at a spatial resolution of $0.0083^\circ \times 0.0083^\circ$. We employ each cell’s population count as a weight to calculate the “center of mass” for each city’s polygon, designating it as the population center.

City leader characteristics data.—To explore heterogeneity with respect to city leaders’ promotion incentives, we employ the methodology of Wang et al. (2020) to measure the promotion probability of a prefecture-level party secretary based on individual characteristics, such as age at assuming office and initial hierarchical level. A higher promotion probability consequently corresponds to higher promotion incentives. We derive these data primarily from the Chinese Political Elite Database (CPED) constructed by Jiang (2018). We then address some missing information with data from Wang et al. (2020) and through manual collection from online news and reports.

5 Monitoring network and pollution elasticity of land price

This section aims to estimate the causal effects of the national atmospheric monitoring network on the elasticity of land price with respect to pollution, which is the parameter ϕ in our theoretical framework. To provide a preliminary insight into the temporal evolution of this pollution elasticity, we start by estimating the following event study specification:

$$\begin{aligned} \ln \text{UnitPrice}_{i,t} = & \alpha_0 + \alpha_1 \cdot \ln \text{Pollution}_{i,t} + \sum_{m=-5}^4 \varphi_m \cdot \ln \text{Pollution}_{i,t} \times \mathbf{1}\{R_{c(i),t} = m\} \\ & + \alpha_2 \cdot \ln \text{Pollution}_{i,t} \times t + \mathbf{X}_i' \boldsymbol{\beta} + \delta_{c(i)} + \varsigma_{p(i),t} + \epsilon_{i,t}, \end{aligned} \quad (10)$$

where $\text{UnitPrice}_{i,t}$ is the unit price for land parcel i transacted in year-quarter t , $\text{Pollution}_{i,t}$ represents the $\text{PM}_{2.5}$ level at the location of parcel i in t , $\mathbf{X}_i$ is a vector of land parcel attributes, including its distance to the city population center, rank, source, transaction mechanism, and buyer’s industry. We incorporate city fixed effects, $\delta_{c(i)}$, to control for intrinsic differences in land market across cities and province–time fixed effects, $\varsigma_{p(i),t}$, to further absorb provincial-level time-varying shocks. Additionally, an interaction term between pollution and a continuous year–quarter trend is included to control for potential linear trends in land prices. We define $R_{c(i),t}$ as the relative quarter with respect to the installation of monitoring stations, which varies across cities in three waves. Specifically, based on the official installation deadlines for each wave, we define the event quarter ($R_{c(i),t} = 0$) as 2012Q4 for Wave 1 cities, 2013Q4 for Wave 2 cities, and 2014Q4 for Wave 3 cities. For the endpoints

of the event window, all observations occurring five or more quarters prior to the event are binned into $R_{c(i),t} = -5$, which serves as the reference period, thus normalizing φ_{-5} to zero. Similarly, all observations four or more quarters after the event are binned into $R_{c(i),t} = 4$. Consequently, the coefficients $\{\varphi_0, \dots, \varphi_3\}$ capture the immediate changes in pollution elasticity subsequent to the monitoring intervention.

Figure 2 presents the estimated coefficients for each of the three waves separately. Across these estimates, only the first wave exhibits an immediate decrease in pollution elasticity, which is notably pronounced during the first quarter of 2013, a period characterized by severe winter pollution. Utilizing the delta method, we estimate the average coefficients for both the pre-monitoring period and the four quarters immediately following monitoring. The point estimates indicate that the pollution elasticity of residential land unit price declines by 0.139 within the initial year subsequent to the intervention. We will further provide a causal estimate for this in subsequent analysis.¹⁶

The observed differential patterns across the three waves may be attributable to the hierarchy-based rollout order of the monitoring network. Wave 1 cities, comprising major metropolitan areas and provincial capitals, are characterized by higher income levels, better education, greater media exposure, and, importantly, higher pollution exposure (see Appendix Figure E.4 for a comparison of $PM_{2.5}$ levels). Residents in these cities are likely more sensitive to newly revealed environmental information and possess a higher willingness-to-pay for clean air. This aligns with the findings in Barwick et al. (2024), which indicate that the effects of monitoring on pollution-avoidance behaviors of residents in Wave 2 cities are smaller and less statistically significant. Inspired by these observations, our subsequent analyses primarily focus on Wave 1 cities.

In Appendix Table E.2, we employ a single dummy variable to denote all post-monitoring periods and estimate a specification analogous to a continuous Difference-in-Differences model. This approach aims to quantify the long-term change in elasticity following monitoring. Consistently, a robust and statistically significant decline in the pollution elasticity of residential land price is observed exclusively in Wave 1 cities, with the magnitude strengthening to approximately -0.25 . It is noteworthy that we also provide estimates for industrial land within this table, for which almost all estimates are small and statistically insignificant. This outcome aligns with the intuition that *ex-ante* pollution may not be a significant determinant in the spatial sorting of industrial activities.

The preceding analyses do not necessarily imply causality due to two primary challenges: the presence of other macroeconomic shocks and the potential endogeneity arising from the monitoring itself influencing pollution levels. We begin by addressing the first challenge. Specifically, the immediate decline in the pollution elasticity of residential land price in Wave 1 cities could be attributed to a macroeconomic shock occurring at the end of 2012, rather than the monitoring network, particularly given the discernible trend observed during 2012Q4 to 2013Q2 in the Wave 2 panel of Figure 2. To address this concern, we leverage the staggered rollout nature of the monitoring network to construct an additional “difference,” thereby ruling out any potential common shocks. Specifically, we

¹⁶A potential concern is that the quarterly pollution level might not be the most appropriate predictor for land prices. In Appendix Figure E.3, we address this by replacing the quarterly $PM_{2.5}$ level with the annual level and re-estimating Equation (10). Reassuringly, the results exhibit patterns consistent with Figure 2, suggesting that the temporal choice of pollution measure does not introduce significant bias into our findings. We continue to utilize the quarterly measure because our subsequent IV estimation relies on inter-quarter variation.

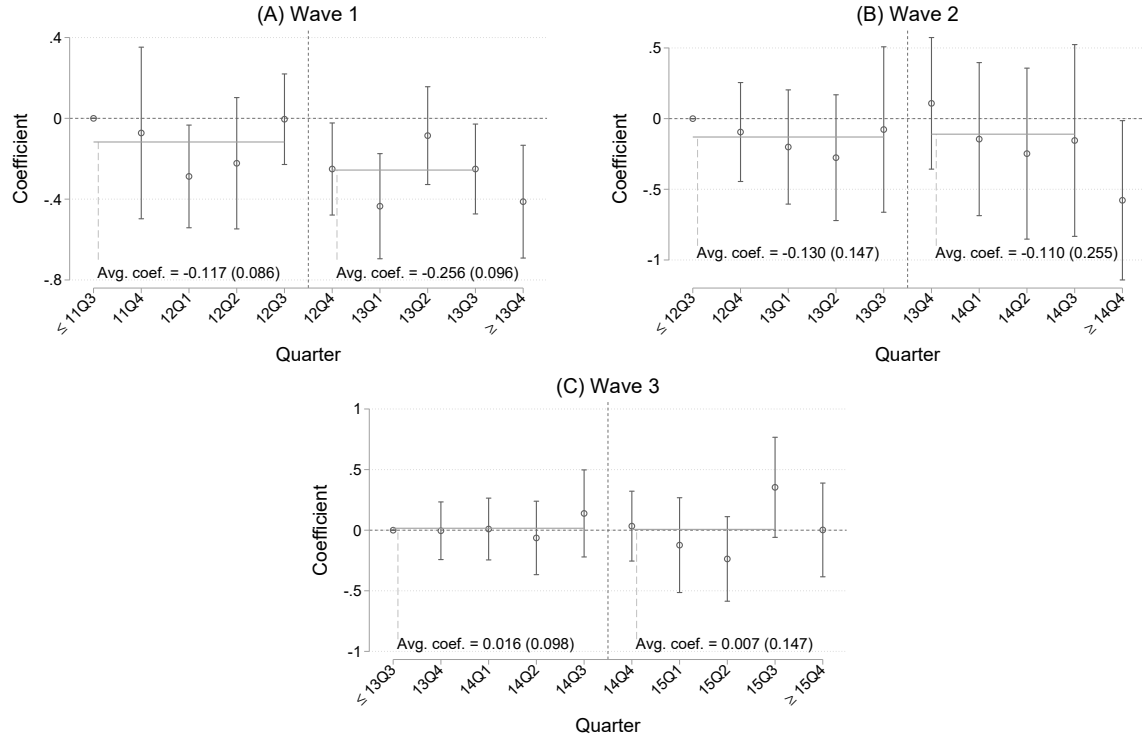


Figure 2: Temporal changes in the pollution elasticity of residential land price for three waves

Notes: This figure illustrates the temporal evolution of the elasticity of residential land price with respect to pollution, derived from estimating Equation (10) separately for cities belonging to each of the three waves of the national rollout. Point estimates are represented by circles, and the lines denote 95% confidence intervals. The average coefficients for both pre-monitoring periods and for the four quarters immediately following monitoring are estimated using the delta method, with their corresponding standard errors reported in parentheses.

estimate the following specification with land transactions before 2013Q4:

$$\begin{aligned} \ln \text{UnitPrice}_{i,t} = & c_0 + \phi \cdot \ln \text{Pollution}_{i,t} \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times \text{After}_t + c_1 \cdot \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times \text{After}_t \\ & + c_2 \cdot \ln \text{Pollution}_{i,t} \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} + c_3 \cdot \ln \text{Pollution}_{i,t} \times \text{After}_t \\ & + c_4 \cdot \ln \text{Pollution}_{i,t} + c_5 \cdot \mathbf{1}\{\text{Wave } 1\}_{c(i)} + c_6 \cdot \text{After}_t + \mathbf{X}'_i \boldsymbol{\beta} + \epsilon_{i,t}. \end{aligned} \quad (11)$$

This specification is similar to a Triple-Differences model, albeit with one dimension of “difference” being a continuous variable, namely $\ln \text{Pollution}_{i,t}$. Specifically, $\mathbf{1}\{\text{Wave } 1\}_{c(i)}$ assumes a value of 1 if the land transaction occurred in cities in the first wave, After_t equals 1 in 2012Q4 and subsequent periods, and other notations retain the same definitions as in Equation 10. Therefore, during the estimated period from 2010Q1 to 2013Q3, cities in the first wave constitute the treatment group, while those in the other two waves serve as the control group. The estimation results, presented in Column (1) of Table 1, suggest an estimate for ϕ of -0.143 .

Due to the hierarchy-based rollout order, it might not be optimal to directly compare all parcels in Wave 1 cities to those in the subsequent two waves. Specifically, the common macroeconomic shocks we aim to eliminate via the additional “difference” might exert heterogeneous impacts across cities with different development levels or among parcels with varying locational attributes. To enhance comparability, we perform parcel matching based on a set of land and city attributes. These attributes include: (i) each parcel’s rank, (ii) source, (iii) transaction mechanism, (iv) buyer’s industry, (v) size, (vi) distance to the city population center, (vii) pollution level at the transaction quarter, (viii) the corresponding city’s GDP per capita, and (ix) population density. It is important to note that attributes (i) through (iv) are discrete variables, which were incorporated as a series of dummy variables in previous regressions, while the remaining attributes are continuous. This distinction drives us to attempt two different matching procedures.

Both matching procedures are performed within year-quarter and land type strata; specifically, parcels in Wave 1 cities are matched with those of the identical land use type (i.e., residential or industrial) that transacted within the same temporal period in Wave 2 and Wave 3 cities. Our first matching procedure consists of two sequential steps: initially, an exact matching is performed based on four discrete covariates; subsequently, within the sample generated by this exact match, the Mahalanobis distance is computed using the continuous covariates, and the four nearest neighbors are identified. While this procedure fully leverages the information of discrete attributes, it occasionally results in a limited pool of control group parcels for the subsequent Mahalanobis distance matching step. As an alternative, the second procedure entails transforming the discrete covariates into a set of dummy variables. These dummy variables are then integrated with all continuous covariates for the calculation of the Mahalanobis distance, following which each parcel is matched with its four nearest neighbors.¹⁷

¹⁷Within a single matching instance for a specific treated parcel, that treated parcel is assigned a weight of 1. For each of the matched control group parcels, a weight is added such that the sum of weights for the control parcels in that specific matching instance equals 1. Specifically, if N control parcels are matched (where N is typically 4), then $1/N$ is added to the weight of each matched control parcel. This ensures that the total weight attributed to the control group equals that of the treated parcel for each match. This proportional adjustment addresses situations where fewer than four control parcels are available (e.g., if only two are matched, each has 0.5 added to its weight) or where more than four are matched due to

Columns (2) and (3) of Table 1 present the results derived from our first matching procedure. We initially estimate the specification outlined in Equation (11), and subsequently employ a more flexible specification wherein $\mathbf{1}\{\text{Wave} = 1\}_{c(i)}$ and After_t are replaced by city and year–quarter fixed effects. Both specifications yield similar and statistically significant point estimates that are substantially larger in magnitude than the full sample estimate, suggesting that national monitoring is associated with a reduction of 0.41 in the pollution elasticity. The results from the second matching procedure are reported in Columns (4) and (5). This procedure, which facilitates the matching of a greater number of parcels in Wave 1 cities, consistently demonstrates a significant reduction in the pollution elasticity of residential land price by 0.25. Moreover, we estimate an event study specification to assess the presence of pre-trends before national monitoring and to explore potential time-varying, post-monitoring effects on the pollution elasticity. As depicted in Figure E.5, no significant pre-trend is observed, and consistent treatment effects are evident immediately following the monitoring.

We conduct three additional analyses complementing the preceding findings. First, we replicate the estimation methodology to investigate the treatment effect on the pollution elasticity of industrial land price in Wave 1 cities, as detailed in Table E.3. The results yield point estimates with small magnitude that are not statistically significant. This finding aligns with our previous conclusions, which suggest that national monitoring is less likely to influence expected fiscal revenues through the transaction price channel.

Second, we address potential concerns regarding the premature installation of monitoring stations in a subset of Wave 2 cities by excluding parcels from Wave 2 cities and utilizing only parcels from Wave 3 cities as the control group. To this end, we re-execute the matching procedure, and the estimation results are presented in Panel A of Table E.4. Columns (1) and (3) employ samples from periods prior to 2013Q3, consistent with the methodology in Table 1. Columns (2) and (4), however, extend the sample period to 2014Q3, thereby incorporating an additional four quarters for estimating the ATT. All columns yield negative and statistically significant causal estimates, ranging from -0.16 to -0.43 . While these point estimates are somewhat smaller than those reported in Table 1, their consistency across different sample periods and control groups underscores the robustness of our primary estimates.

Finally, we estimate the treatment effects for Wave 2 cities by comparing parcels in Wave 2 cities to those in Wave 3 cities. The results are presented in Panel B of Table E.4. With the application of the first matching procedure, the estimated causal effects, while statistically significant, are found to be smaller in magnitude compared to those observed for Wave 1 cities. When the second matching procedure is subsequently employed, the effect becomes statistically insignificant. Later, when instrumental variables for pollution and its interaction terms are further employed, we again find insignificant estimates. These results suggest that any effect of national monitoring in Wave 2 cities, if present, is likely to be substantially weaker.

As previously mentioned, a second potential threat to our identification strategy stems from endogeneity concerns, which could bias the coefficient estimate even after controlling for other confounding shocks. To clarify, our primary identification concern centers on the potential endogeneity

ties in the Mahalanobis distance (e.g., if multiple parcels share the fourth-nearest distance).

Table 1: ATT of national monitoring on the pollution elasticity of residential land price in Wave 1 cities

	Dependent variable: Logarithm of unit price of land parcel				
	Full sample	Two-step matching		Mahalanobis matching	
	(1)	(2)	(3)	(4)	(5)
$\ln(\text{PM}_{2.5}) \times \text{Wave 1} \times \text{After}$	-0.143 [*] (0.087)	-0.425 [*] (0.233)	-0.412 ^{**} (0.181)	-0.243 [*] (0.128)	-0.252 ^{***} (0.083)
$\text{Wave 1} \times \text{After}$	0.476 (0.322)	1.433 [*] (0.842)	1.416 ^{**} (0.635)	0.846 (0.522)	0.912 ^{***} (0.332)
$\ln(\text{PM}_{2.5}) \times \text{Wave 1}$	0.156 (0.153)	0.598 ^{***} (0.224)		0.514 ^{**} (0.199)	
$\ln(\text{PM}_{2.5}) \times \text{After}$	-0.077 (0.060)	0.197 (0.224)		0.015 (0.113)	
$\ln(\text{PM}_{2.5})$	0.141 [*] (0.081)	-0.280 [*] (0.155)		-0.184 (0.124)	
Wave 1	0.148 (0.591)	-1.841 ^{**} (0.896)		-1.533 [*] (0.807)	
After	0.573 ^{***} (0.210)	-0.348 (0.809)		0.235 (0.465)	
Controls	Yes	Yes	Yes	Yes	Yes
$\ln(\text{PM}_{2.5}) \times \text{year-quarter FEs}$	No	No	Yes	No	Yes
$\ln(\text{PM}_{2.5}) \times \text{city FEs}$	No	No	Yes	No	Yes
Year-quarter fixed effects	No	No	Yes	No	Yes
City fixed effects	No	No	Yes	No	Yes
# of clusters	327	286	286	286	286
# of parcels in Wave 1 cities	104,606	93,311	93,311	104,605	104,605
# of observations	352,787	155,677	155,677	182,484	182,484

Notes: This table presents estimates of the average treatment effect of national monitoring on the pollution elasticity of residential land price in Wave 1 cities, derived from estimating Equation (11). Column (1) reports estimates obtained using the full sample, while Columns (2) to (5) utilize samples constructed via two distinct matching procedures. Both procedures were conducted within year-quarter and land type strata. The first procedure commenced with an initial exact matching on four discrete covariates (e.g., rank, transaction mechanism). Subsequently, within the exactly matched sample, Mahalanobis distance matching was then applied utilizing continuous covariates (e.g., distance to the population center, pollution level). The second procedure involved transforming discrete covariates into dummy variables, which were subsequently integrated with all continuous covariates for the purpose of Mahalanobis distance matching. In both cases, each parcel was matched with its four nearest neighbors, where applicable. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of the triple-interaction term, rather than merely the intrinsic endogeneity of the pollution variable itself. Indeed, $\ln Pollution_{i,t}$ is recognized as an endogenous variable. For instance, unobservable amenities, exhibiting highly granular variation, can simultaneously influence both pollution levels and the attractiveness of residential land parcels. Consequently, the positive estimates for α_1 in Appendix Table E.2 and c_4 in Table 1 do not accurately reflect the underlying causal parameters.

However, as demonstrated by Barwick et al. (2024), consistent estimation of ϕ remains feasible even when $\ln Pollution_{i,t}$ exhibits endogeneity, contingent upon the satisfaction of two specific *sufficient* conditions. First, conditional on control variables, the treatment status indicator, $\mathbf{1}\{\text{Wave } 1\}_{c(i)} \times After_t$, must be independent of the unobserved residential land price determinants, $\epsilon_{i,t}$. This condition is posited to hold based on two arguments. Firstly, as outlined in the background section, the rollout order of monitoring stations was largely determined by pre-existing city hierarchies and designated statuses. Consequently, it is unlikely those unobserved determinants influenced the rollout sequence, especially after controlling for city fixed effects. Secondly, since the installation of monitoring stations represents an intervention primarily targeting environmental regulation, we reasonably anticipate that its impact on residential land prices operates exclusively through pollution-related mechanisms. These mechanisms are explicitly captured in our model specification, thus preventing their manifestation in the error term. The second sufficient condition stipulates that, conditional on control variables, the treatment status indicator must be independent of the pollution level, $\ln Pollution_{i,t}$. Satisfying this condition is considerably more stringent, given that the monitoring intervention itself has the potential to alleviate air pollution (Xie and Yuan, 2023; Yang et al., 2024).

To further examine these identification concerns and the requisite conditions for consistent estimation, we conduct a Monte Carlo simulation, as detailed in Appendix B. The simulation yields two salient implications. First, the estimated coefficient for the triple-interaction term remains consistent even when monitoring exerts a homogeneous, one-time treatment effect on pollution levels; however, this consistency no longer holds if treatment effects exhibit spatial or inter-temporal heterogeneity. Second, the employment of a valid instrumental variable for pollution permits the simultaneous attainment of consistent estimates for both the triple-interaction term and the pollution variable itself.¹⁸

Informed by these implications, we utilize the frequency of the thermal inversion phenomenon as an instrumental variable for pollution levels to further validate our estimates. This instrument has been widely used in the literature (e.g., Arceo et al., 2016; Fu et al., 2021; Chen et al., 2024). Thermal inversions occur when a layer of warm air overlies cooler surface air, forming a meteorological “lid” that suppresses vertical mixing. By preventing the natural convective dispersion of emissions, this phenomenon traps pollutants near the ground, causing pollution concentrations to rise signif-

¹⁸In Appendix C, we provide an explicit estimation of the immediate treatment effects of monitoring on PM_{2.5} concentration during the four quarters subsequent to the establishment of automatic monitoring stations in Wave 1 cities. The findings from our estimation corroborate the conclusions presented in Yang et al. (2024). Specifically, we observe that while monitoring may not exert a statistically significant aggregate pollution reduction effect across the entire city, its impacts exhibit significant spatial heterogeneity. In the short term, local governments appear to strategically concentrate regulatory enforcement efforts in areas proximate to monitoring stations to mitigate pollution increases, potentially resulting in a concurrent relaxation of enforcement in regions more distal from monitors.

icantly even when local emission rates remain constant. Its exogenous nature as a meteorological phenomenon largely ensures its validity as an instrumental variable for pollution levels. Details on the construction of this variable are provided in Appendix A.4. A binscatter plot illustrating the correlation between $PM_{2.5}$ concentration and the frequency of thermal inversion is presented in Appendix Figure E.6. This figure demonstrates a significant, approximately linear relationship between the two variables.

With this instrument, we re-estimate equation (11) using the Two-Stage Least Squares estimator. In this framework, the pollution variable and all its interaction terms are treated as endogenous. We then construct a corresponding set of instrumental variables where the pollution variable in each endogenous term is replaced by the thermal inversion frequency. We report the estimation results in Table 2. Notably, the point estimates for the triple-interaction term are consistently negative and statistically significant, exhibiting a larger magnitude than those reported in Table 1. Furthermore, to ensure robust inference in the presence of a relatively small first-stage F-statistic, we adopt the method proposed by Lee et al. (2022) to calculate the “0.05 tF standard error” for each estimate, which are reported in brackets. Even with these inflated standard errors, statistical significance is maintained, particularly for the two estimates derived from the matching sample.

Table 2: Estimating ATT on the pollution elasticity of residential land price with instrumental variables

	Dependent variable: Logarithm of unit price of land parcel		
	Full sample	Two-step matching	Mahalanobis matching
	(1)	(2)	(3)
$\ln(PM_{2.5}) \times \text{Wave 1} \times \text{After}$	−0.356** (0.170) [0.269]	−0.981*** (0.336) [0.467]	−0.830*** (0.263) [0.363]
$\ln(PM_{2.5})$	−0.494*** (0.192) [0.304]	−1.324*** (0.316) [0.439]	−1.245*** (0.340) [0.470]
Controls	Yes	Yes	Yes
Kleibergen–Paap F-statistic	12.219	17.308	17.609
# of clusters	327	286	286
# of parcels in Wave 1 cities	104,606	93,323	104,606
# of observations	352,789	155,689	182,485

Notes: This table reports estimates of the average treatment effect of national monitoring on the pollution elasticity of residential land price in Wave 1 cities. Estimates are derived from Equation (11) using the Two-Stage Least Squares estimator. The frequency of thermal inversion serves as the instrumental variable for pollution, and is subsequently utilized to construct instruments for the endogenous interaction terms. For clarity, only the estimated coefficients of two key variables are presented in this table, though all other relevant variables are incorporated into the estimation. Standard errors, clustered at the city level, are reported in parentheses. The “0.05 tF standard errors” proposed by Lee et al. (2022) are calculated and reported in brackets.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, marked based on standard errors in parentheses.

Additional regression results employing this instrument are reported in Appendix Tables E.5 and E.6. Once again, we observe that monitoring does not significantly alter the pollution elasticity of

industrial land price. Furthermore, the preceding findings remain robust when using only parcels in Wave 3 cities as the control group, although the point estimates show a substantial increase in magnitude, potentially related to the weakening of the instrumental variables. Finally, the treatment effects on pollution elasticity in Wave 2 cities are no longer found to be statistically significant.

To conclude this section, which has centered on providing an estimate for ϕ to facilitate subsequent analyses of local governments' land supply decisions, we summarize the 95% confidence intervals for all estimates obtained herein in a single plot of Appendix Figure E.7. It is observed that the value of -0.32 is encompassed by the majority of these confidence intervals. Therefore, for our subsequent analyses, this value is adopted as the estimate for ϕ , indicating that national monitoring leads to an average decrease of 0.32 in the pollution elasticity of residential land prices in Wave 1 cities.

6 Fiscal revenues and pollution increases of land supply

This section advances to the second and third steps of our empirical analysis, dedicated to estimating the differences in expected fiscal revenue and pollution increments between industrial and residential land uses. As established in the background section, zoning decisions are made by local governments prior to the public announcement of each land parcel's availability. Consequently, local governments plausibly form their expectations solely on the basis of a land parcel's attributes and location. Therefore, our estimations attempt to estimate the post-monitoring differences between these two land use types as functions of a set of observable attributes in our dataset.

6.1 Difference in expected fiscal revenues

We commence with the estimation of the difference in expected fiscal revenue between industrial and residential land uses. Within the theoretical framework, it is assumed that local governments' decisions concerning land use type are solely predicated on the expected fiscal revenue from land supply prior to monitoring. Furthermore, the coefficients within both the post-monitoring revenue functions (i.e., Equations (6) and (7)) are assumed to remain invariant relative to the pre-monitoring function (i.e., Equation (2)). The singular exception to this invariance is the pollution elasticity of residential land, the modification of which was estimated in the preceding section.¹⁹ These foundational assumptions allow for the estimation of differences in the coefficients of the revenue functions between two land types, utilizing land supply decisions observed in Wave 1 cities before monitoring. To mitigate the influence of systematic temporal variations in these coefficients, this estimation is specifically confined to four immediately preceding quarters (i.e., 2011Q4 to 2012Q3).

¹⁹In subsequent analyses, empirical evidence will be provided to support these two assumptions. Regarding the first assumption, after estimating the pollution increases of industrial land, we incorporate this variable as an additional explanatory factor, alongside fiscal revenue, in the model for pre-monitoring land type choices. However, its estimated coefficient is found to be statistically insignificant and quantitatively minor. For the second one, we compare the estimated coefficients in the revenue functions derived from two distinct samples—transactions during the first and second pre-monitoring years in Wave 1 cities. We observe that these coefficients exhibit a strong correlation, thereby suggesting robust short-term stability.

Within the discrete choice model, the probability that a parcel is designated for industrial use is established by Equation (3). With assuming that the difference between the unobserved utility components, $\varepsilon_{n,i,R,t}^0 - \varepsilon_{n,i,I,t}^0$, follows a standard normal distribution, a probit model is employed for the estimation. To address the endogeneity inherent in the pollution variable, we again utilize the frequency of the thermal inversion phenomenon as an instrument. Column (1) of Table 3 presents the results derived from the IV-probit estimator, where the dependent variable is a dummy indicating industrial land supply. The independent variables include PM_{2.5} concentrations, distance to the city population center, a set of discrete attributes (including land rank, source, and transaction mechanism), as well as city and quarter fixed effects.

As anticipated, the point estimate for PM_{2.5} concentration is positive. This indicates that, controlling for other attributes, a higher pollution level is associated with a greater expected fiscal revenue differential when a parcel is designated for industrial use compared to residential use. This finding aligns with our previous observation that pollution negatively impacts the transaction price of residential land. Furthermore, the fiscal revenue differential is greater for parcels situated farther from the city center. This observation can be partially attributed to the typically higher housing prices in city centers, which leads to a steeper distance gradient in residential land price (see Appendix Figure A.6). In contrast, the expected future tax revenues generated by an industrial firm are likely to be less sensitive to its proximity to the city center.

Table 3: Estimating the difference of expected fiscal revenues between two land types

Dependent variable:	1{Industrial land}	Logarithm of unit price
	(1)	(2)
ln(PM _{2.5})	0.875** (0.419)	-0.581*** (0.164)
ln(Distance to population center)	0.086** (0.037)	-0.416*** (0.053)
<i>Discrete attributes:</i>		
Land rank	Yes	
Land source	Yes	
Land transaction mechanism	Yes	
City dummies	Yes	
Quarter dummies	Yes	
Controls		Yes
Estimator	IV-probit estimator	2SLS estimator
# of observations	37,905	83,761

Notes: Column (1) presents estimates from the probit model based on Equation (3). The estimation sample comprises all land transactions in Wave 1 cities from 2011Q4 to 2012Q3. The frequency of the thermal inversion phenomenon is employed as an instrumental variable for the pollution measure. Column (2) reports estimates derived from a 2SLS estimator, using the same instrumental variable for pollution. The estimation sample for Column (2) consists of nationwide residential land transaction records from 2011Q4 to 2012Q3. The dependent variable is the logarithm of the price per unit area of residential land. Control variables include land rank, land source, and transaction mechanism. Standard errors, clustered at the city level, are reported in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1.

It should be emphasized that the point estimates derived from the probit model represent the

product of the coefficient differences in the revenue functions and the preference parameter α^0 . Consequently, the predicted values based on the coefficients in Column (1) of Table 3 reflect the expected fiscal revenue differential scaled by α^0 . To address this, we calibrate α^0 using the point estimate for $\ln Pollution_{i,t}$ of 0.875, which quantifies the term $\alpha^0(\gamma^I - \gamma^R)$. Here, γ^I and γ^R represent the pollution elasticities of industrial and residential land revenues, respectively. As discussed in the background section, land transaction income constitutes a predominant component of fiscal revenues from residential land, implying that γ^R specifically reflects the pre-monitoring pollution elasticity of residential land price.

In Column (2) of Table 3, we estimate this elasticity by utilizing all residential land transaction records from 2011Q4 to 2012Q3. A 2SLS estimator is employed, with the thermal inversion frequency serving as the instrument for pollution. The derived estimate for γ^R is -0.581 . This value is close to the estimate presented in Column (1) of Table 2 derived from a Triple-Differences model, suggesting that prior to monitoring and pollution information disclosure, a 1% increase in the pollution level was associated with approximately a 0.58% decrease in residential land price.

The magnitude of our estimated pollution elasticity for residential land price is comparable to findings in the existing literature. Although direct estimates for the pollution elasticity of land price are limited, several studies provide estimates for the pollution elasticity of housing price in China, from which the corresponding elasticity of land price can be inferred.²⁰ For instance, Chen and Jin (2019) report that a 1% increase in $PM_{2.5}$ concentrations is associated with a 0.24% reduction in local housing prices. Similarly, Ou et al. (2022) document a housing price elasticity of -0.32 . Utilizing the estimate from Wu et al. (2012), which indicates that land transaction prices account for, on average, 37% of total house values, the implied pollution elasticities of residential land price from these two studies are approximately -0.649 and -0.865 , respectively.

In contrast, fiscal revenues derived from industrial land primarily represent anticipated future tax receipts. Consequently, γ^I is interpreted as quantifying the pollution elasticity of industrial production. The magnitude of this impact has been extensively studied in the literature, although the findings are mixed (e.g., Chang et al., 2019; He et al., 2019; Fu et al., 2021; Cook and Heyes, 2022; Hansen-Lewis, 2026). In a study for China, He et al. (2019) report a statistically significant, albeit modest, adverse effect: a sustained increase of $10 \mu g/m^3$ in $PM_{2.5}$ concentration (approximately a 20% increase relative to 2012 levels) over a 3–4 week period results in a 0.5% to 1% reduction in worker output, implying an elasticity ranging from -0.05 to -0.025 . Similarly, Chang et al. (2019) derive an elasticity of -0.023 . However, Fu et al. (2021) estimate a substantially larger value of -0.17 for the pollution elasticity of value-added. More recently, Hansen-Lewis (2026), focusing

²⁰Following Ahlfeldt et al. (2015), we assume a competitive construction sector that utilizes residential land K and capital M as inputs. The production function is $H = M^\mu K^{1-\mu}$, where $1 - \mu$ represents the share of land cost in the total construction cost. In a competitive equilibrium, the unit price of housing equals its unit construction cost, which can be shown to be $p_h = \gamma r^\mu p_l^{1-\mu}$, where r denotes the exogenous capital price, p_l represents the unit land price, and γ is a constant. Consequently, taking the logarithm of this expression yields:

$$\ln p_l = \frac{1}{1-\mu} \ln p_h - \frac{\mu}{1-\mu} \ln r - \frac{1}{1-\mu} \ln \gamma.$$

If the pollution elasticity of housing price is denoted by γ^h , then the pollution elasticity of residential land price, γ^R , is therefore $\gamma^R = \gamma^h / (1 - \mu)$.

on India, elucidate how technological choices influence this pollution elasticity, a mechanism that potentially accounts for the existing mixed evidence. For the purpose of our calibration, we select a moderate value of -0.1 .

Using the estimated values of -0.581 for γ^R , -0.1 for γ^I , and 0.875 for $\alpha^0(\gamma^I - \gamma^R)$, we calibrate α^0 to be 1.819 . This calibrated value, combined with all point estimates derived from the probit model, allows for the recovery of coefficient differences between industrial and residential land uses within the revenue functions. Subsequently, by substituting these pre-monitoring estimates, along with the estimated causal parameter ϕ , into Equation (8), we estimate the expected fiscal revenue differential for all parcels transacted in the four quarters immediately following monitoring (2012Q4 to 2013Q3) in Wave 1 cities.²¹ These estimates are graphically presented in Appendix Figure E.8.

Finally, to support this extrapolation, we conduct a test to assess the short-term stability of the coefficients in the expected fiscal revenue function. Specifically, we utilize land transaction records from the second year preceding automatic monitoring in Wave 1 cities to re-estimate Equation (3) using the identical probit model. If the coefficients exhibit short-term stability, we would anticipate a strong correlation between the coefficients derived from samples in the first and second pre-monitoring years. The results are presented in Appendix Figure E.9. Given the potential for varying preference parameters across these two periods, we scale all coefficients from the earlier sample by a uniform factor to equate their estimates for the coefficient of $\ln Pollution_{i,t}$. The figure reveals a strong positive correlation, evidenced by an R-squared value exceeding 0.8 and a fitted line closely approximating the 45° line.

6.2 Pollution increases of industrial land

The subsequent step is to estimate the expected *ex-post* pollution levels associated with the supply of land parcels. Analogously, we aim to derive a function representing the difference in counterfactual pollution levels between two land use types, $\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}$, determined by a set of land attributes and fixed effects. Under the assumption that local governments' expectations are grounded in empirical realities, this function can be estimated using our land dataset. However, a key challenge lies in the unobservability of the expected counterfactual pollution level, $Pollution'_{i,j,t}$.²² This level is distinct from the observed pollution level in grid cell g , where parcel i is located, at post-transaction year-quarter τ . Specifically, this observed level, denoted as $\ln Pollution_{g(i),\tau}^{obs}$, would be confounded by any underlying time trends or exogenous shocks occurring during the period $\tau - t$.

²¹To clarify, the quantity estimated from these coefficients is precisely $\ln V_{n,i,I,t}^1 - \ln V_{n,i,R,t}^1 - \ln(1 - \tau_{c(i)})$. This distinction arises because city-specific treatment effects of monitoring on total industrial production have not been identified and are subsequently absorbed by city fixed effects in our regressions for local governments' objective function.

²²The notation here deviates slightly from its strict theoretical definition. In the theoretical framework, this term represents the expected counterfactual pollution level attributable to a *unit* land parcel i , which is consistent with the treatment of fiscal revenue per unit parcel as another determinant in land type decisions. However, to align with the observed land transaction data, the notation in this empirical context refers to the counterfactual pollution level generated by the *entire* parcel. Subsequently, when regressing the difference in pollution levels as a function of land attributes, land size will be incorporated as a control variable. Furthermore, when estimating the expected pollution difference, we condition on a unit land size.

Formally, we assume that

$$\ln Pollution_{g(i),\tau}^{\text{obs}} = \ln Pollution'_{i,j,t} + \delta_{c(i)} \times T_t(\tau, Pollution_{g(i),t}) + \epsilon_{g(i),\tau}, \quad (12)$$

where $\delta_{c(i)}$ denotes city fixed effects and it interacts with a time trend function, $T_t(\tau, Pollution_{g(i),t})$. The time trend is contingent on observed time τ and the initial pollution level $Pollution_{g(i),t}$ in the location of parcel i . Collectively, this interaction term posits that areas with differing initial pollution levels may exhibit distinct city-specific time trends. This formulation reflects the fact that each local government may have its own incentive to impose differential regulatory enforcement across areas characterized by varying environmental pressures. Additionally, $\epsilon_{g(i),\tau}$ denotes an orthogonal idiosyncratic error term, which accounts for individual shocks.

Industrial production constitutes the primary source of particulate matter in China; conversely, residential use of urban land is typically associated with significantly lower pollution emissions.²³ Consequently, to facilitate our estimation, we adopt an assumption that the counterfactual increase in pollution attributable to residential land use is negligible. This implies that $\ln Pollution'_{i,R,t} = \ln Pollution_{g(i),t}$. Under this assumption, our objective shifts to quantifying $\ln Pollution'_{i,I,t} - \ln Pollution_{g(i),t}$, which represents the expected pollution increases of industrial land.

For grid cells in city c that do not undergo a land transaction, we associate each with a hypothetical non-transacted parcel $i' \in O_c$ to maintain consistent notation. The observed pollution levels for these non-transacted grid cells are thus given by:

$$\ln Pollution_{g(i'),\tau}^{\text{obs}} = \ln Pollution_{g(i'),t} + \delta_{c(i')} \times T_t(\tau, Pollution_{g(i'),t}) + \epsilon_{g(i'),\tau}. \quad (13)$$

In this context, the initial pollution level, $\ln Pollution_{g(i'),t}$, serves as the counterfactual pollution level. Next, consider a subset $O_c(i) \subset O_c$ comprising N_i parcels (grid cells) that share the same initial pollution level at time t as parcel i , i.e., $Pollution_{g(i'),t} = Pollution_{g(i),t}$ for all $i' \in O_c(i)$. With subset $O_c(i)$, we derive the following equation:

$$\ln Pollution_{g(i),\tau}^{\text{obs}} - \frac{1}{N_i} \sum_{i' \in O_c(i)} \ln Pollution_{g(i'),\tau}^{\text{obs}} = \ln Pollution'_{i,I,t} - \ln Pollution_{g(i),t} + u_{i,\tau}, \quad (14)$$

where $u_{i,\tau} \equiv \epsilon_{g(i),\tau} - \frac{1}{N_i} \sum_{i' \in O_c(i)} \epsilon_{g(i'),\tau}$. This difference effectively eliminates the common city-specific time trend, leaving a residual combination of idiosyncratic shocks.

Ultimately, our objective is to estimate $\ln Pollution'_{i,I,t} - \ln Pollution_{g(i),t}$ as a function of specific land attributes and fixed effects. We specify it as a linear function, such that $\ln Pollution'_{i,I,t} - \ln Pollution_{g(i),t} = M'_{i,t}\rho$, where $M_{i,t}$ represents a vector of all relevant explanatory variables. Substituting this specification into Equation (14) yields our regression equation:

$$\ln Pollution_{g(i),\tau}^{\text{obs}} - \frac{1}{N_i} \sum_{i' \in O_c(i)} \ln Pollution_{g(i'),\tau}^{\text{obs}} = M'_{i,t}\rho + u_{i,\tau}. \quad (15)$$

²³According to the Second Census of Polluting Sources in 2017, industrial emissions account for 75.44% of the total emissions of particulate matter. Details can be found at https://www.mee.gov.cn/xxgk2018/xxgk/xxgk01/202006/t20200610_783547.html.

Given that the combined idiosyncratic error term $u_{i,\tau}$ is orthogonal to the vector of explanatory variables $M_{i,t}$, i.e., $\mathbb{E}[M_{i,t}u_{i,\tau}] = 0$, the parameter vector ρ can be consistently estimated using OLS.

Empirically, for the construction of a set of comparable cells for each industrial parcel, we utilize the quarterly pollution panel dataset, which provides $\text{PM}_{2.5}$ concentrations for an average of 12,505 grid cells in each Wave 1 city. The post-transaction period, τ , for the regression is subsequently defined as the third year following the transaction year-quarter t (i.e., $\tau = t + 12$). To mitigate potential confounding effects from pollutant spillovers originating from adjacent grid cells undergoing industrial land transactions during this three-year period, a 2.5-kilometer buffer zone was delineated around each industrial land parcel transacted between 2012Q4 and 2016Q3. Grid cells situated within these buffer zones were excluded, and the remaining cells form the set O_c for each city. Following this exclusion process, an average of 10,435 cells remained per city.

For each industrial land parcel i within city c , transacted between 2012Q4 and 2013Q3, we identify cells i' from the set O_c that satisfy the initial $\text{PM}_{2.5}$ concentration difference criterion: $-1 < \text{Pollution}_{g(i),t} - \text{Pollution}_{g(i'),t} < 1$. These selected non-transacted cells constitute the control group $O_c(i)$ for parcel i , subsequently utilized to compute the left-hand side of Equation (15). On average, 1,001 cells are matched to each industrial land parcel, with the mean initial $\text{PM}_{2.5}$ concentration difference being $0.058 \mu\text{g}/\text{m}^3$.

Utilizing these matched control groups, we construct two distinct time series for each industrial land parcel: the logarithm of its own $\text{PM}_{2.5}$ concentration and the mean logarithm of $\text{PM}_{2.5}$ concentrations from its designated control group grid cells. Subsequently, the difference between these two time series is computed to derive each industrial parcel's individual pollution increase trajectory across relative quarters $\tau \in \{t - 8, \dots, t + 20\}$. These trajectories, encompassing approximately 16,800 industrial parcels, are then averaged, with the aggregate results presented in Figure 3. The figure indicates an absence of a systematic trend in pollution levels prior to the land transaction. Following the land transaction, however, pollution levels exhibit a discernible ramp-up trend over the subsequent three years. This period is consistent with the typical timeframe for firms' production development and operational scaling. Subsequently, pollution levels appear to stabilize after the third year, which suggests that firms have reached their full production capacity on the respective land parcel. On average, the supply of an industrial land parcel is associated with a 3% increase in the $\text{PM}_{2.5}$ concentration within its locating grid cell. Furthermore, the observed pattern in this figure lends support to our selection of $\tau = t + 12$ for subsequent analyses.

After computing the dependent variable of Equation (15) using non-transacted grid cells as the control group, we proceed to regress it against a set of land attributes, alongside city and quarter fixed effects. The estimation results are presented in Column (1) of Table 4. The logarithm of land size is incorporated as an explanatory variable to account for the potential scale effect of production on pollution increases. Consistent with expectations, a positive coefficient estimate is obtained for the land size, suggesting that larger industrial parcels are associated with a greater increment in pollution. Furthermore, the regression reveals that industrial parcels situated at a greater distance from city population centers exhibit a comparatively smaller increase in pollution.

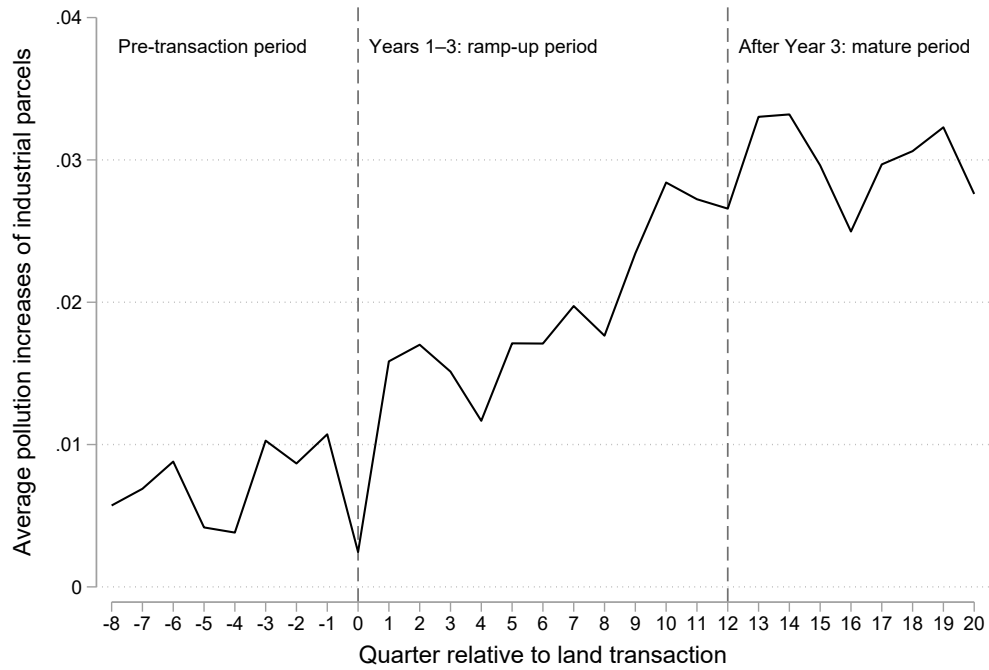


Figure 3: Average pollution increase trajectory of industrial land parcels over time

Notes: This figure illustrates the average pollution increase of transacted industrial land parcels relative to the pollution levels of non-transacted control cells, calculated using the left-hand side of Equation (15). Initially, for each industrial land parcel transacted between 2012Q4 and 2013Q3 in Wave 1 cities, we construct two time series: the logarithm of its $PM_{2.5}$ concentration and the mean logarithm of $PM_{2.5}$ concentrations from its corresponding control group grid cells. Subsequently, we compute the difference between these two time series to derive each industrial parcel's individual pollution increase trajectory. Finally, we average these approximately 16,800 industrial parcels' trajectories by relative quarter and present the results in this figure.

Utilizing the estimates from Column (1), we predict the expected difference in counterfactual pollution levels between the two land use types for each parcel transacted during 2012Q4 to 2013Q3 in Wave 1 cities. To ensure alignment with prior estimations for the fiscal revenue difference per unit parcel, all predictions for the pollution difference are conditional on a unit land size (i.e., setting $\ln LandSize_i = 0$ for each parcel). We graphically present these results in Appendix Figure E.10.

The assumption of negligible pollution increases resulted from residential use permits the utilization of a substantially larger pool of non-transacted grid cells, thereby enhancing the comparability of the control group for counterfactual pollution estimation. Alternatively, absent this assumption, we could directly quantify the difference $\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}$ by matching residential land parcels to each industrial land parcel. However, the considerably more constrained pool of eligible residential parcels for matching could impede the achievement of high comparability. The econometric justification and matching procedure are detailed in Appendix D.1. Employing this alternative method, we re-estimate Equation (15), with the results reported in Columns (2) to (4) of Table 4. Specifically, Column (2) utilizes all industrial parcels, whereas Columns (3) and (4) restrict the sample to industrial parcels matched with a residential parcel, where the absolute difference in $PM_{2.5}$ concentration in the transaction year-quarter is less than $5 \mu g/m^3$ and $1 \mu g/m^3$, respectively. Consistent patterns emerge across all these specifications. An extended discussion of these four sets of estimated coefficients is provided in Appendix D.1, which illustrates the general consistency of the derived pollution difference predictions.

Another related concern is that matching based on the pollution level of a single quarter and estimating counterfactual pollution levels from a single post-transaction quarter may be susceptible to confounding from quarter-specific shocks. To address this, Appendix D.2 outlines an alternative procedure utilizing four-quarter average pollution levels for both matching and estimation. As anticipated, this procedure yields predictions with a smaller variance. In the subsequent section, when employing the predicted counterfactual pollution differential to estimate local governments' utility function, we confirm the robustness of our findings to these two alternative methods.

7 Post-monitoring incentives of local governments

In this section, we advance to the final stage of our empirical analysis: quantifying the trade-off between the objectives of fiscal revenue and environmental protection within local governments' utility functions. Building upon this, we further investigate the spatial strategic behaviors and heterogeneity influenced by city leaders' characteristics.

7.1 Trade-off between fiscal revenues and environmental protection

Leveraging the estimates for $\ln V^1_{n,i,I,t} - \ln V^1_{n,i,R,t}$ and $\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}$, obtained for each land parcel transacted during 2012Q4 to 2013Q3 in Wave 1 cities in the preceding section, we can estimate the preference parameters α^1 and θ^1 specified in Equation (9). Consistent with the assumption adopted for the pre-monitoring utility, we posit that the difference in unobserved components, $\varepsilon^1_{n,i,R,t} - \varepsilon^1_{n,i,I,t}$, follows a standard normal distribution, and consequently, a probit

Table 4: Estimating the difference of expected pollution levels between two land use types

	Dependent variable: Observed pollution increases			
	vs. Grid cells	vs. Residential land parcels		
		Full sample	Initial diff. < 5	Initial diff. < 1
			(3)	(4)
	(1)	(2)	(3)	(4)
ln(Land size)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
ln(Distance to population center)	-0.013*** (0.003)	-0.011*** (0.003)	-0.011*** (0.003)	-0.013*** (0.004)
<i>Discrete attributes:</i>				
Land rank	Yes	Yes	Yes	Yes
Land source	Yes	Yes	Yes	Yes
Land transaction mechanism	Yes	Yes	Yes	Yes
City dummies	Yes	Yes	Yes	Yes
Quarter dummies	Yes	Yes	Yes	Yes
# of observations	16,722	16,770	15,945	11,057

Notes: This table presents the estimation results for Equation (15). Column (1) employs non-transacted grid cells as the control group to quantify the left-hand side of Equation (15), while Columns (2) to (4) utilize transacted residential parcels as the control group. Column (2) includes all industrial parcels, whereas Columns (3) and (4) restrict the sample to industrial parcels matched with a residential parcel, where the absolute difference in PM_{2.5} concentration in the transaction year-quarter is less than 5 µg/m³ and 1 µg/m³, respectively. Standard errors, clustered at the city level, are reported in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1.

model is employed for the estimation. City fixed effects are incorporated to account for the city-specific treatment effects of monitoring on industrial production, $\ln(1 - \tau_{c(i)})$.²⁴

The estimation results are presented in Table 5. As discussed in the theoretical framework, the identifiable parameters, α^1 and θ^1 , reflect the underlying preference parameters of local governments, but scaled by a positive factor related to the standard deviation of the unobserved utility component. Consequently, an individual estimated coefficient offers only qualitative insights regarding its corresponding component within the objective function. For instance, Column (1) reveals a statistically significant positive point estimate for fiscal revenue and a negative point estimate for pollution. This implies that higher fiscal revenues and lower counterfactual pollution levels associated with a particular land use type contribute to greater utility.

Crucially, however, their ratio, θ^1/α^1 , effectively eliminates this common scaling factor, thereby directly quantifying the underlying relative importance of the environmental protection objective compared to the fiscal revenue objective within the utility function. The point estimate and its standard error for this ratio are computed using the delta method and are also reported in the table. In Column (1), the estimated ratio is found to be -6.373 . This suggests that, on average, the utility derived from a 6.373% increase in a land parcel's fiscal revenues is equivalent to the disutility incurred from a 1% increase in the pollution level within its associated geographic cell.

In Wave 1 cities during 2012, the average transaction price for a residential land parcel was approximately 20 million CNY per hectare (see Appendix E.2). Concurrently, the average size of industrial land parcels stood at 3.392 hectares. Given that an average 3% increase in pollution levels was observed three years following the transaction of an industrial land parcel (see Figure 3), a unit hectare of land is consequently associated with a 0.884% increase in cell PM_{2.5} concentration. Considering that the population-weighted PM_{2.5} concentration for Wave 1 cities in 2012 was 50 $\mu\text{g}/\text{m}^3$ (see Appendix Figure E.4), this percentage increase translates to an absolute rise of 0.442 $\mu\text{g}/\text{m}^3$. Utilizing our estimated quantitative relationship between fiscal revenue loss and pollution reduction, the elimination of these induced pollutants implies that local governments are willing to forgo 5.634% ($= 6.373 \times 0.884\%$) of the fiscal revenues from this unit parcel, which corresponds to approximately 1.127 million CNY in absolute terms. Furthermore, the average population density in Wave 1 cities in 2012 was 485.11 people per 1 km^2 land, which is approximately equivalent to the area of a grid cell with a spatial resolution of $0.01^\circ \times 0.01^\circ$. Collectively, these findings indicate that, on average, local governments are willing to incur a cost of 2,323.18 CNY per person for a 0.442 $\mu\text{g}/\text{m}^3$ reduction in PM_{2.5} concentration. This is equivalent to 5,256.06 CNY (approximately 832 USD at 2012 exchange rates) per person for a 1 $\mu\text{g}/\text{m}^3$ decline.

For comparative purposes, Freeman et al. (2019) estimated residents' willingness-to-pay for air quality with a spatial sorting model, reporting that in 2005, a median household would be willing to pay 21.70 USD for a 1 $\mu\text{g}/\text{m}^3$ decline in annual PM_{2.5} concentration. Adjusting for inflation in

²⁴For robustness checks, Appendix Table E.7 presents results derived from alternative estimation methods, including the logit model, linear probability model, and PPML estimator. While these models operate under distinct distributional assumptions for the unobserved term, leading to variations in the individual point estimates across methods, the ratio between the two point estimates, which is our primary quantitative result of interest, remains highly consistent with the findings from the probit model.

China between 2005 and 2012, this 21.70 USD in 2005 is equivalent to 27.13 USD in 2012.²⁵ This value is substantially lower than our estimated willingness-to-pay by local governments.

Improvements in air quality within a specific grid cell can generate positive externalities for surrounding cells, thus benefiting a larger population. To account for this broader impact, we consider a generous scenario where the air quality improvement originating from a single land parcel induces a uniform decrease in PM_{2.5} concentration across a 2.5-kilometer radius region. This range is consistent with the buffer zone constructed for filtering out clean non-transaction cells. In this scenario, the number of beneficiaries is 19.63 ($= 3.14 \times 2.5^2$) times greater than that within a single cell. Consequently, local governments' willingness-to-pay per person reduces to 42.41 USD for a 1 $\mu\text{g}/\text{m}^3$ decline, which, nonetheless, remains considerably larger than the estimated residents' willingness-to-pay. These findings suggest that, following the central government's intensified monitoring and regulation in 2012, local governments, facing political pressure, exhibit significantly stronger incentives for pollution reduction compared to the personal willingness of residents to pay.

In Column (2), we perform an adjustment to the estimated pollution differential for robustness checks. During the estimation of counterfactual pollution levels between the two land use types, 4,423 parcels (approximately 9.13% of the total) yielded negative pollution predictions from the linear model (i.e., Equation (5)). To align with the empirical expectation that industrial land parcels typically generate higher pollution, these negative values are subsequently truncated to zero. As observed in Column (2), this adjustment introduces negligible changes, resulting in a ratio of -7.002 with a slightly increased magnitude.

Column (3) further incorporates quarter fixed effects to address potential concerns regarding inter-quarter comparison. While city fixed effects appropriately isolate the analysis to within-city variations, recognizing that each local government operates as an independent decision-maker for its own jurisdiction, the estimation in Column (1) pools all land type decisions made across the four examined quarters. On one hand, the temporal variation in pollution levels provides additional identification leverage. Specifically, a robust pattern indicates that local governments tend to reduce the supply of industrial land during the first and fourth quarters, periods typically characterized by elevated pollution levels. On the other hand, inter-quarter variations could also arise from periodic political factors, such as local governments frequently aiming to increase transaction volumes in the fourth quarter to meet annual zoning plan targets. Consequently, Column (3) examines the robustness of our findings to these inter-quarter variations. In this specification, the estimated ratio is found to be -3.126 . While this represents a reduction in its absolute magnitude compared to the baseline, it retains both economic and statistical significance. Moreover, even when utilizing this smaller ratio, the accounting results derived from the assumed generous scenario continue to imply a higher willingness-to-pay by local governments compared to that of residents.

To further validate our findings, we present two additional sets of robustness results. First, we conduct a falsification test to investigate whether environmental protection had already emerged as a priority for local governments prior to the implementation of the monitoring program. Specifically,

²⁵According to China's National Bureau of Statistics, the annual CPI from 2006 to 2012 are 101.5, 104.8, 105.9, 99.3, 103.3, 105.4, and 102.6, respectively. Therefore, this implies 1 CNY in 2005 is comparable to 1.25 CNY in 2012. Here we ignore the temporal change in the exchange rate between CNY and USD.

Table 5: Estimating post-monitoring utility function of local governments

	Dependent variable: $\mathbf{1}\{\text{Industrial land}\}$		
	(1)	(2)	(3)
Difference in fiscal revenues	1.232*** (0.100)	1.229*** (0.100)	1.575*** (0.100)
Difference in pollution levels	-7.849*** (1.712)		-4.923** (2.009)
Difference in pollution levels (≥ 0)		-8.605*** (1.917)	
Estimated θ^1/α^1	-6.373	-7.002	-3.126
Standard error for estimated θ^1/α^1	1.404	1.574	1.273
City fixed effects	Yes	Yes	Yes
Year-quarter fixed effects	No	No	Yes
# of clusters	73	73	73
# of observations	48,422	48,422	48,422

Notes: This table presents the estimation results of Equation (9) using a probit model. The explanatory variables are the differences in expected fiscal revenue and counterfactual pollution levels between industrial and residential land use, as estimated in Section 6. The estimation sample comprises all land parcels transacted in Wave 1 cities during the period of 2012Q4 to 2013Q3. In Column (2), negative values of the estimated pollution differential for parcels are truncated to zero. Standard errors, clustered at the city level, are reported in parentheses. The ratio of the two point estimates, representing θ^1/α^1 , is also reported, with its standard error calculated using the delta method.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

we employ the estimated coefficients from Column (1) of Table 3 (and set ϕ to zero) to predict the fiscal revenue differentials between industrial and residential land use for parcels transacted in Wave 1 cities during the four quarters immediately preceding the monitoring phase (i.e., 2011Q4–2012Q3). Following the procedure detailed in Section 6.2, we estimate a pollution function by comparing each parcel with a set of comparable grid cells to predict each parcel’s expected pollution differential. Utilizing these estimates, we then estimate Equation (9) using these pre-monitoring transaction records. This test is also replicated for parcels transacted during the second pre-monitoring year (i.e., 2010Q4–2011Q3) in Wave 1 cities. The results, reported in Appendix Table E.8, exhibit consistent patterns across both pre-monitoring periods: while higher fiscal revenues remain positively associated with utility, the estimated coefficients for the pollution differential are largely statistically insignificant and markedly smaller in magnitude compared to the post-monitoring estimates. One marginally significant point estimate is even positive, further suggesting that environmental protection was not a primary concern for local governments before the central government intensified monitoring and enforcement efforts.

Second, we examine the sensitivity of the results to the methodologies employed for predicting the difference in counterfactual pollution levels. To this end, the predicted pollution differentials are substituted with those derived from the two alternative methods introduced in Section 6.2. Estimation results are reported in Appendix Table E.9, where the majority of the estimated ratios are consistent with our baseline findings.

7.2 Spatial strategic behaviors: a ring analysis

As Yang et al. (2024) highlight, the pollution reduction efforts of local governments tend to be localized. Building on this insight, we further demonstrate that these efforts are driven by spatially heterogeneous incentive structures among local governments. To this end, we conduct a ring analysis based on the distance of each parcel to the nearest monitoring station within its respective city. Specifically, we construct a set of dummy variables, $\mathbf{D}_i \equiv \{D_i^{0-3}, D_i^{3-6}, D_i^{6-9}, D_i^{9-12}, D_i^{12-20}, D_i^{20-30}, D_i^{30-40}\}$. For example, D_i^{0-3} equals 1 if the distance between parcel i and the nearest monitoring station in its city is between 0 km and 3 km, and 0 otherwise. We then restrict our estimation sample to parcels located within 40 kilometers and interact these dummy variables with all included regressors. This approach is equivalent to estimating separate models for each distance-based subsample.

Figure 4 presents the results of the ring analysis. For each distance bin, point estimates for θ^1 and α^1 are derived. Their ratio and corresponding 95% confidence interval are then quantified using the delta method. Consequently, this figure illustrates the relative importance local governments place on environmental protection compared to fiscal revenue, stratified by the distance to the nearest monitoring station. As observed, the post-monitoring incentives of local governments exhibit significant spatial heterogeneity. At locations within the 0–3 km radius of a monitoring station, where the central government’s monitoring intensity is expected to be highest, local governments prioritize pollution abatement most strongly. The estimated coefficient ratio of -8.236 is substantially larger in absolute magnitude than the baseline result. However, this relative importance of environmental protection diminishes within the 3–6 km bin and becomes statistically insignificant at greater distances.

These findings indicate that, despite the higher willingness-to-pay for clean air observed among local governments compared to residents in our earlier estimations, this incentive is spatially localized. As monitoring intensity diminishes, this willingness-to-pay significantly attenuates, frequently becoming statistically indistinguishable from zero. Consequently, the national automatic monitoring program, implemented since 2012, has introduced a critical new dimension to regional environmental inequality in China, wherein proximity to monitoring stations now serves as a salient determinant of local governments’ environmental prioritization.

Moreover, two falsification tests are conducted to further validate the ring analysis. First, we replicate the ring analysis using parcels transacted prior to the implementation of monitoring, with the results presented in Appendix Figure E.11. In this pre-monitoring period, as monitoring stations had not yet been established, we do not anticipate observing a significant spatial gradient with respect to the locations of these future monitoring stations. As depicted in the figure, all point estimates for the parameter ratios are positive and generally consistent, with some exhibiting statistical significance. These positive estimated parameter ratios, which stem from positive point estimates for the pollution variable, are consistent with the aggregate estimates presented in Appendix Table E.8. This suggests that, prior to the prioritization of environmental protection, higher counterfactual pollution levels may indicate a larger scale of production and, consequently, higher expected future tax revenues. In this context, the pollution variable likely served as an additional proxy for economic activity desired by local governments, complementing the fiscal revenue variable.

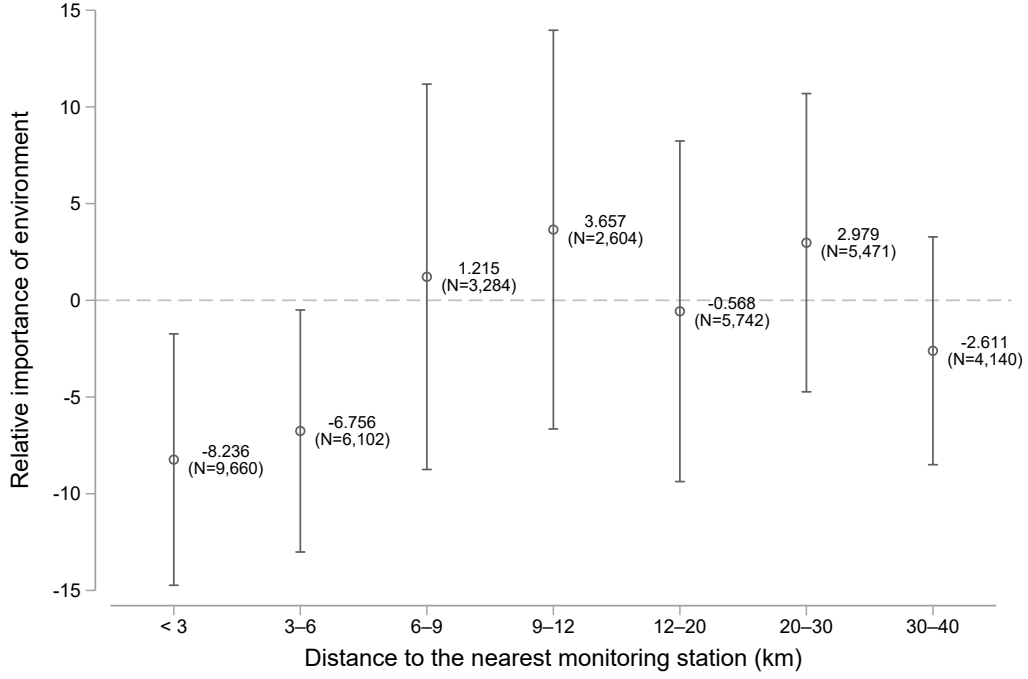


Figure 4: Ring analysis based on the distance to the nearest monitoring station

Notes: This figure illustrates the results of a ring analysis stratified by the distance to the nearest monitoring station. Standard errors, clustered at the city level, are employed for estimation. Full regression results are reported in Appendix Table E.10. In this figure, each dot represents the ratio of two point estimates, specifically $\hat{\theta}^1$ (for pollution) and $\hat{\alpha}^1$ (for fiscal revenue) corresponding to a specific distance bin. For instance, the dot in the first column depicts the ratio between the estimated coefficient on $(\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}) \times D_i^{0-3}$ and the estimated coefficient on $(\ln V^1_{n,i,I,t} - \ln V^1_{n,i,R,t}) \times D_i^{0-3}$. Each line indicates the corresponding 95% confidence interval, computed using the delta method. The exact point estimates and the number of land parcels in each subsample are presented directly in the figure.

Second, we replace the distance to the nearest monitoring station with the distance to the city population center and re-estimate the ring analysis specification. The results are presented in Appendix Figure E.12. The distance bins were slightly adjusted to avoid insufficient observations in certain bins. Unlike the original monitoring station-based stratification, the bins in this figure do not inherently reflect monitoring intensity. Consequently, despite a potential correlation between these two distance metrics, no similar spatial pattern is observed in this figure. This finding lends support to the interpretation that the observed spatial heterogeneity reflects the strategic behaviors of local governments in response to central government monitoring activities.

7.3 Heterogeneity with respect to leader characteristics

Finally, we examine the heterogeneity in incentives concerning city leaders' characteristics, with a particular focus on their historical emphasis on environmental protection and promotion incentives.

7.3.1 Historical environmental emphasis

To quantify local leaders' historical environmental emphasis, we adapt the methodology developed by Chen et al. (2024), constructing a measure derived from local governments' annual work reports. Specifically, we manually collected all annual work reports from Wave 1 cities for 2011, the year preceding the initiation of automatic monitoring.²⁶ Using a predefined set of environment-related keywords, we then computed the frequency of these keywords within each report. This metric is subsequently employed to measure each city's historical environmental prioritization.

To ensure the keyword set we defined is comprehensive and accurate for identifying environment-related terms, we employed *gemini-2.5-flash*, a Large Language Model (LLM) developed by Google, to identify and label environmental protection-related terms within each report.²⁷ Subsequent to the LLM's identification of all relevant keywords in each report, these identified terms were aggregated into a comprehensive list. From this aggregate list, we then extracted the 10 most frequent keywords pertaining to general environmental protection. Sorted by frequency, these are: *huanjing* (environment), *shengtai* (ecology), *jieneng* (energy saving), *jianpai* (emission reduction), *huanbao* (environmental protection), *wuran* (pollution), *lvse* (green), *huanjing baohu* (environmental protection), *nenghao* (energy consumption), and *paifang* (emission). Additionally, we extracted another 10 most frequent keywords directly related to air pollutants and air quality. These include: *ditan* (low-carbon), *qingjie* (clean energy), *eryanghualiu* (SO₂), *yangchen* (dust), *kongqi* (air), *ranmei* (coal-fired), PM_{2.5}, *danyanghuawu* (NO_x), *daqi* (atmosphere), and *guolu* (boiler). Utilizing

²⁶These reports were issued by prefectural governments during prefectural People's Congresses at the beginning of 2012.

²⁷The prompt utilized (translated from the original Chinese) was: "You are a professional policy text analyst. I now want to measure local governments' emphasis on air pollution through text analysis of government work reports. I will provide you with the text of government work reports. Please carefully analyze the report text and identify all keywords related to atmospheric environment and air pollution. When making judgments, be sure to refer to the context to ensure accurate understanding of word meanings (for example, the word 'environment' in 'network environment' should not be considered a relevant keyword). I need you to return the original text in markdown format, marking the keywords you find with asterisks (*). Do not return any other content or explanations beyond the annotated original text." In some cases, the LLM identified multi-word phrases; consequently, we employed the Python *jieba* library to further segment these into shorter terms.

these two sets of keywords, we construct two different metrics. The first metric is the frequency (defined as the number of keywords per 1,000 Chinese characters) of all 20 identified keywords, which serves to reflect the emphasis on general environmental protection affairs. The second metric is the frequency of the 10 air pollution-specific keywords, providing a more focused indicator of governmental attention to air quality.²⁸

Table 6 reports the results from probit models where these two normalized keyword frequency metrics are incorporated as interaction terms with the primary explanatory variables. In both columns, we observe a statistically significant and negative coefficient for the interaction term with the pollution variable. This finding suggests that a greater historical emphasis on environmental protection corresponds to an increased willingness of local governments to prioritize cleaner air after automatic monitoring. Specifically, as presented in Column (2), a one standard deviation increase in keyword frequency from its mean value leads to an increase in the absolute magnitude of the coefficient ratio (θ^1/α^1) from -6.169 to -8.742 .

Table 6: Heterogeneity in post-monitoring incentives: historical emphasis on environmental protection

	Dependent variable: $\mathbf{1}\{\text{Industrial land}\}$	
	All keywords	Air pollution-related keywords
	(1)	(2)
Difference in fiscal revenues	1.228*** (0.098)	1.239*** (0.100)
Difference in pollution levels	-7.800*** (1.654)	-7.644** (1.672)
Diff. in fiscal revenues $\times$ Keyword frequency	-0.089 (0.070)	-0.110* (0.062)
Diff. in pollution levels $\times$ Keyword frequency	-2.919** (1.223)	-2.226* (1.295)
City fixed effects	Yes	Yes
# of clusters	73	73
# of observations	48,422	48,422

Notes: This table presents the results from a probit model, investigating the heterogeneity in local governments' post-monitoring incentives with respect to their historical emphasis on environmental protection. The explanatory variables are the differences in expected fiscal revenue and counterfactual pollution levels between industrial and residential land use, as estimated in Section 6. Keyword frequency serves as a moderator variable, measured by the frequency of environment-related keywords in government work reports for 2011. Column (1) utilizes all 20 identified keywords, whereas Column (2) employs only the 10 specifically air pollution-related keywords. The moderator variable is standardized (mean of zero, standard deviation of one) in both columns. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

²⁸We refrain from directly utilizing the LLM's raw keyword labels for direct counting, as ensuring consistent labeling criteria across diverse report texts proved challenging. For instance, the LLM labeled nearly all phrases containing the word *shengtai* (ecology) in the Urumqi report, whereas only a limited number were labelled in the Guiyang report. A methodological concern associated with our adopted approach—utilizing the LLM to construct a keyword list and subsequently calculating keyword frequencies—is the potential for context-dependent ambiguity in certain general terms, such as “environment” when used in phrases like “network environment.” This concern is largely mitigated by our second metric, which is constructed solely from the 10 specifically air pollution-related keywords, as these terms are inherently less ambiguous in context.

Additionally, we categorize Wave 1 cities into two groups based on the median keyword frequency and subsequently estimate the ring analysis specification for each subsample. The results, presented in Appendix Figure E.13, reveal evidence of more pronounced spatial strategies adopted by local governments with a higher historical emphasis on environmental protection. Specifically, the coefficient ratios in areas within a 6-kilometer range of a monitoring station are substantially larger in absolute magnitude (< -10) in the high frequency group, and then revert more sharply to become statistically indistinguishable from zero in more distant areas. By contrast, most coefficient ratios in the low frequency group are negative, and their variation is notably smaller. These findings collectively suggest that, in the context of intensified central government monitoring, cities with a stronger historical emphasis on environmental protection tend to engage in more pronounced and spatially strategic pollution reduction efforts, reflecting a sophisticated adaptation rather than uniform compliance with central directives.

7.3.2 Political promotion incentive

Next, we examine another salient characteristic of local leaders within the Chinese context: their political promotion incentives. To construct this incentive measure, we collected biographical information for the party secretary (*shiweishuji*) of each city in 2012.²⁹ This data was sourced from the datasets of both Jiang (2018) and Wang et al. (2020), supplemented by additional data from online news and reports.

Based on a similar dataset for party secretaries spanning from 2000 to 2011, Wang et al. (2020) estimate a baseline probit model predicting a city leader's promotion likelihood as a function of their initial age and hierarchical rank at the commencement of office, along with their interaction term. Their extended model further incorporates two dummy variables indicating whether a city leader previously worked in the central government and possessed a graduate degree. Leveraging these established estimates, we predict the promotion likelihood for each party secretary in Wave 1 cities in 2012. This predicted likelihood then serves as our measure for their promotion incentives. Further details regarding the construction of this measure are provided in Appendix Section A.6.

Table 7 presents the results from interacting our measures of political promotion incentive with the expected differences in fiscal revenues and counterfactual pollution levels, revealing consistent findings across both columns. Specifically, we observe that leaders with higher promotion incentives exhibit a lower willingness-to-pay for improved air quality. Based on the point estimates in Column (2), a one standard deviation increase in promotion incentive from its mean value is associated with a decrease in the absolute magnitude of the coefficient ratio (θ^1/α^1) from -6.416 to -4.883 .

This finding suggests that, despite the formal integration of environmental protection into local officials' performance evaluations, the superior measurability and broader visibility of fiscal revenues and economic development indicators likely remain more dominant and influential metrics for political promotion. This consequently attenuates incentives for genuine environmental improvements. This implication is further supported by a subsample analysis, employing a similar ring

²⁹Following Wang et al. (2020), we designate the city's party secretary as the city leader, acknowledging the party secretary's superior authority over the city mayor due to the dominant political position of the Communist Party of China.

Table 7: Heterogeneity in post-monitoring incentives: political promotion incentive

	Dependent variable: $\mathbf{1}\{\text{Industrial land}\}$	
	Baseline measure	Extended measure
	(1)	(2)
Difference in fiscal revenues	1.235*** (0.091)	1.234*** (0.092)
Difference in pollution levels	-7.924*** (1.687)	-7.916** (1.698)
Diff. in fiscal revenues $\times$ Promotion incentive	0.196** (0.083)	0.175** (0.084)
Diff. in pollution levels $\times$ Promotion incentive	0.937 (1.652)	1.257 (1.659)
City fixed effects	Yes	Yes
# of clusters	73	73
# of observations	48,422	48,422

Notes: This table reports the results of a probit model, examining the heterogeneity in local governments' post-monitoring incentives in relation to their political promotion incentives. The explanatory variables are the estimated differences in expected fiscal revenue and counterfactual pollution levels between industrial and residential land uses, as detailed in Section 6. Promotion incentive serves as a moderator variable, calculated based on the estimated coefficients from probit models in Wang et al. (2020), as detailed in Appendix Section A.6. Column (1) employs their baseline model, which predicts promotion likelihood based on a leader's initial age and hierarchical rank at the commencement of office, along with their interaction term. Column (2) utilizes their extended model, additionally incorporating two dummy variables indicating whether a city leader previously worked in the central government and held a graduate degree. The moderator variable is standardized (mean of zero, standard deviation of one) in both columns. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

analysis specification and presented in Appendix Figure E.14, which reveals that leaders with higher promotion incentives tend to adopt more pronounced spatial strategic behaviors.

8 Conclusions

This paper investigates the transformation of local governance incentives in China following the centralization of pollution monitoring authority. By bridging the gap between reduced-form evidence and structural quantification, we recover the parameters of local governments' utility function through the lens of land use type decisions. Our findings document a fundamental shift: the introduction of non-manipulable monitoring stations successfully introduced a significant shadow price for pollution into the objective function of local officials. We estimate that, on average, local governments are willing to sacrifice approximately 6.37% of expected fiscal revenue from a land parcel to avoid a 1% increase in local $\text{PM}_{2.5}$ concentrations. This implies an estimated willingness-to-pay for clean air by local governments of approximately 832 USD per person (or, more conservatively, 42.41 USD, when assuming substantial externalities) for a $1 \mu\text{g}/\text{m}^3$ reduction. Nevertheless, we also document significant spatial strategic behaviors: this willingness diminishes sharply beyond 6 kilometers from monitoring stations.

Our structural estimates reveal the distinct nature of China's "war on pollution." The estimated government shadow price for clean air substantially exceeds the private willingness-to-pay of residents found in the literature. This discrepancy underscores that the recent improvement in air quality is not a response to bottom-up market demand, but rather a product of intense top-down political pressure. Consequently, our estimated parameter effectively captures the government's pricing of accountability.

While this demonstrates that centralized regimes can rapidly mobilize resources to address externalities, the welfare implications are nuanced. On one hand, when political valuation far outstrips social valuation, it implies a potential distortion: local agents may over-invest in visible pollution control at the expense of other welfare-enhancing public goods. On the other hand, as noted by Greenstone and Jack (2015), residents in developing countries may undervalue clean air due to income levels or policy failures. From this perspective, a higher government valuation could serve a corrective, paternalistic role to rectify market under-pricing. Distinguishing between these two interpretations—political distortion versus paternalistic correction—remains a critical avenue for future research aiming to determine the socially optimal level of environmental accountability.

Additionally, our findings on spatial strategic gaming expose a fundamental paradox in the digitization of governance. While the automatic monitoring network seemingly solved the problem of information asymmetry regarding data veracity, it failed to resolve the deeper issue of incentive incompatibility. Indeed, the intense top-down pressure may have exacerbated these distortions, illustrating a spatial manifestation of Goodhart's Law: when a measure (monitoring station readings) becomes a target, it ceases to be a good measure of the underlying latent variable (overall air quality). This has profound distributional implications. Since monitoring stations are typically located near population centers, localizing abatement efforts around them may benefit the majority. How-

ever, this strategy inherently creates a new dimension of spatial environmental inequality, effectively pushing pollution to the periphery and amplifying administrative boundary effects of pollution.

Therefore, while the national automatic monitoring network is a pivotal achievement, it is not a panacea for environmental governance in decentralized regimes. To mitigate these strategic distortions, supplementary mechanisms are essential. First, as highlighted by Zou (2021) and Yang et al. (2024), remote sensing data can serve as a “space-truthing” audit. While less precise than ground stations, the universal coverage of satellite data eliminates the blind spots necessary for spatial gaming. Second, empowering bottom-up monitoring is crucial. Recent evidence suggests that public appeals through social media can effectively curb violations (Buntaine et al., 2024). As public awareness rises—facilitated by the data transparency from the monitoring network—harnessing this societal pressure may prove to be the critical missing link in achieving genuine, city-wide environmental compliance.

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A Additional data description and construction

A.1 Land transaction data

Our land transaction data are sourced from the China Land Market (<https://landchina.com>), a website administered by China's Ministry of Natural Resources. This website serves as the official repository for all historical land transaction records dating back to 1989 and is widely utilized in studies concerning China's land market and urban planning. For our analysis, we utilize transaction records spanning from 2010 to 2018.

A.1.1 Land attributes

For each land transaction record, our dataset includes 15 attributes: project name, address, electronic supervision number (*dianzi jianguan hao*), transaction price, land size, source, use type, transaction mechanism, rank, buyer's name and industry, transaction date, agreed land transfer date, agreed construction start date, and agreed construction completion date. From the transaction date attribute, we extract the year, quarter, and month for each record. Utilizing the Baidu Map API (<https://api.map.baidu.com/>), we subsequently derive the coordinates (longitude and latitude) of each land parcel based on its address attribute.

We provide further elucidations for the following five attributes:

- **Electronic supervision number (*dianzi jianguan hao*):** Each land transaction is assigned a unique electronic supervision number, typically comprising 16 digits. For instance, a land parcel transacted in Yingtan, Jiangxi Province, on July 6, 2010, bears the number “3606812010B00178.” The initial six digits (“360681”) encode the administrative region: the first two digits designate the provincial-level administrative region (e.g., “36” for Jiangxi Province, whose full code is “360000”); the subsequent two digits identify the prefecture-level administrative region within that province (e.g., “06,” which, when combined with “36,” forms “3606” for Yingtan, Jiangxi Province, with a full code of “360600”); and the final two digits specify the county-level administrative region within that prefecture (e.g., “81,” completing the code “360681” for Guixi, Yingtan, Jiangxi Province).¹ Given that these six digits directly correspond to administrative regions down to the county level, we leverage them to pinpoint the province and city of each parcel's location. The subsequent four digits of the electronic supervision number (“2010”) indicate the transaction year. The ensuing digit (“B”) represents the business type code (*yewu ma*); for example, “B” signifies a land transaction business. Finally, the twelfth to fifteenth digits constitute the serial number, and the last digit serves as a check digit.
- **Land source:** Land sources for construction parcels are categorized into three types: newly added construction land, newly added construction land from stock inventory, and existing

¹A comprehensive list delineating each administrative region and its corresponding code is accessible at <https://www.mca.gov.cn/mzsj/xzqh/2023/202301xzqh.html>.

construction land. The first category, newly added construction land, refers to land converted from agricultural or underutilized land for construction purposes within the current year. This type is critically subject to the strict constraint of the annual land use quota. The second category, newly added construction land from stock inventory, refers to land that received agricultural conversion approval in previous years but was subsequently held in the government’s land reserve. The third category, existing construction land, refers to the reallocation or redevelopment of land already legally classified as construction land (e.g., through the revitalization of old industrial sites or urban renewal). Unlike the first category, this type does not involve the conversion of farmland and is therefore exempt from agricultural conversion quota constraints.

- **Land use type:** As introduced in Section 2.2, urban construction land is classified into eight types based on the *Current Land Use Classification (2007)*. It is important to note that while this standard was revised at the end of 2017, this eight-type classification scheme remained consistent. These categories include commercial land, industrial land, residential land, public administration and service land, special land, transportation land, water bodies and hydraulic facilities land, and unclassified land. Of these eight types, commercial land, industrial land, and residential land collectively account for over 95% of all transaction records; consequently, we aggregate all other types into a single “other” category. Following the common approach in the literature, we also combine commercial land and residential land into a single type, termed “residential land” for simplicity. This aggregation is justified because they share highly similar mechanisms for contributing to local governments’ fiscal revenues, primarily through higher transaction income generated from land sales. Thus, they stand in contrast to industrial land, which primarily generates fiscal revenues through long-term tax collection. In summary, in our analysis, all land parcels are categorized into three types: industrial land, residential (and commercial) land, and other land. When exploring the land type decision of local governments, we disregard the “other” category and focus on the fundamental trade-off between industrial land and residential (and commercial) land.
- **Transaction mechanism:** Our dataset primarily features five transaction mechanisms: listing (*guapai*), administrative allotment (*huabo*), agreement (*xieyi*), auction (*paimai*), and tender (*zhaobiao*). These mechanisms account for 38.65%, 28.93%, 25.67%, 6.26%, and 0.24% of the raw transaction data, respectively, from 2010 to 2018. Among these, three are considered market-oriented: listing, which refers to a two-stage auction process; auction, which specifically denotes an English auction; and tender, which represents a sealed-bid auction (Tian et al., 2024). The “agreement” mechanism entails bargaining between the local government and the land buyer, though with a lower degree of competitive intensity compared to the three market-oriented methods. Finally, administrative allotment, by its nature, is not a market-based transaction. It typically involves no monetary payment and is reserved for public or non-commercial purposes.
- **Land rank:** The rank (or tier) of each land parcel is intrinsically linked to a national reform

initiated in January 2007. In an effort to curb intense race-to-the-bottom competition for investments fueled by exceedingly low industrial land prices, the central government instituted a minimum price standard for industrial land sales. Specifically, all counties were categorized into 15 distinct ranks, with a corresponding minimum unit price stipulated for each. For instance, based on the 2007 standard, the minimum price for the highest rank was 840 CNY/m², while that for the lowest rank was 60 CNY/m². Consequently, the land rank serves as a direct determinant of the unit transaction price, particularly for industrial land parcels.

A.1.2 Data cleaning

The raw dataset comprises 1,678,077 land transaction records spanning the period from 2010 to 2018. Our data cleaning process consists of the following six steps, ultimately yielding a dataset with 1,071,842 transaction records suitable for our empirical analysis:

1. To ensure precise geographic identification, we commence by standardizing province and city names and rectifying administrative codes based on the initial four digits of the electronic supervision number. Subsequently, we exclude approximately 2.3% of parcels that could not be matched with any prefecture-level administrative regions. This exclusion primarily pertains to parcels within special functional zones—such as the Xinjiang Production and Construction Corps—whose land supply incentives diverge from those of typical local governments. This procedure yields a sample comprising 1,638,311 records.
2. We perform a spatial cross-validation to ensure consistency between the nominal administrative location and the coordinates derived from the Baidu Map API. Specifically, all parcels are projected into a Geographic Information System (GIS). By performing a spatial join with an official prefecture-level polygon map, we verify whether each parcel falls within its listed administrative boundary. Approximately 1.9% of the records are excluded where the physical coordinates do not match the administrative records (e.g., due to severe coordinate errors or data entry mistakes), resulting in a final sample of 1,607,462 records.
3. We further refine the dataset by removing records with critical missing information. We exclude parcels with missing or zero land area and those lacking essential transaction details, such as land use, buyer's industry, and transaction mechanism. Crucially, to ensure our price-related analysis, we remove records with missing transaction prices, which constitute approximately 16.7% of the remaining sample. After these exclusions, 1,335,227 records remain.
4. Following the common approach in the literature, for example, He et al. (2022), we restrict our analysis to market-oriented or semi-market-oriented transaction mechanisms, specifically including listing (*guapai*), tender (*zhaobiao*), auction (*paimai*), and agreement (*xieyi*). We explicitly exclude administrative allotment (*huabo*), as these transactions typically involve no monetary payment and are utilized for public or non-commercial purposes. This restriction reduces the sample to 1,143,373 records.

5. Finally, we standardize the land use descriptions into 9 primary categories based on the national standard *Current Land Use Classification* and classify the industry of the land buyer according to the *Industrial Classification for National Economic Activities*. After excluding records with unidentified use types or industry classifications, our final analytical sample consists of 1,071,842 observations. The geographical distribution of these parcels are presented in Figure A.1.

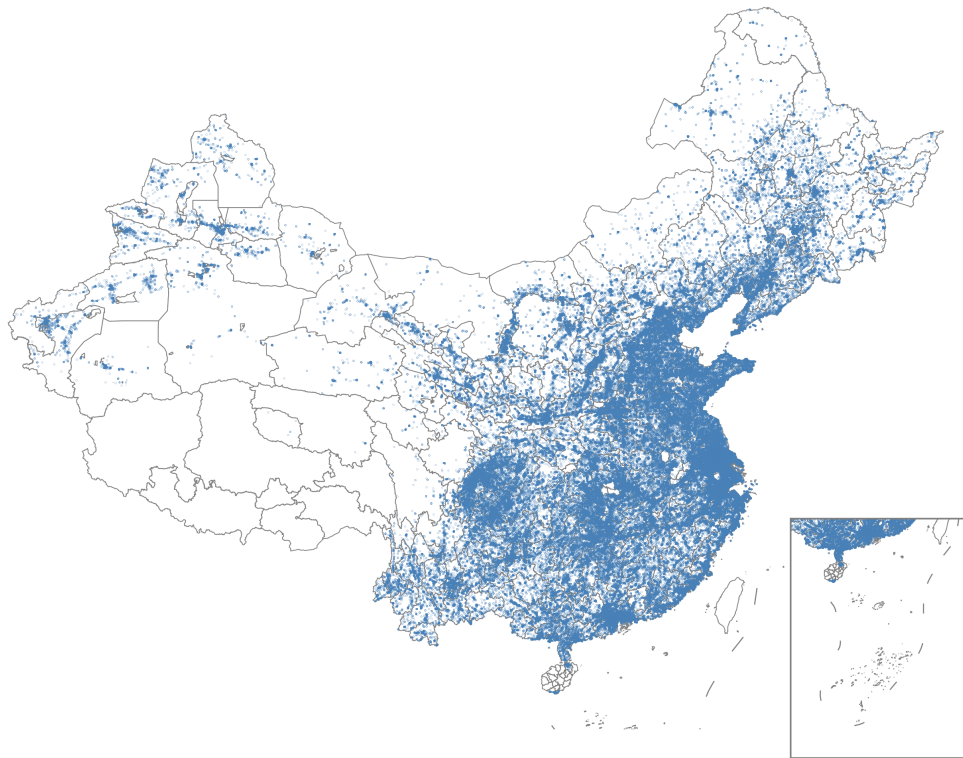


Figure A.1: Location of land parcels in our dataset

Notes: This figure illustrates the spatial distribution of the 1,071,842 land parcel transactions recorded in our dataset from 2010 to 2018. Each dot represents a distinct transaction. The dataset encompasses 4 direct-administered municipalities (provincial-level cities) and 324 out of 333 prefecture-level administrative regions, covering 30 of the 34 provincial-level administrative regions. The four provincial-level administrative regions not included in our dataset are Xizang Autonomous Region, Hong Kong Special Administrative Region, Macao Special Administrative Region, and Taiwan Province.

A.2 Monitoring station data

This dataset is sourced from the Hong Kong University of Science and Technology Atmospheric and Environmental Database, which provides information including names, geographical coordinates, cities, open years of 1,499 monitoring stations opened during 2012 to 2014. After dropping 6 stations that can not be concisely matched to a specific prefecture-level administrative regions, 1,493 of them remain in our dataset in use.

We present the geographical distribution of monitoring stations in Figure A.2. This figure also illustrates the location of each city's population center, the calculation process for which will be elaborated in Section A.5. As discussed in Section 2.1, the placement of monitoring stations aims to optimally reflects the average pollution level within urban areas. This is further evidenced in Figure A.2, where we observe that the location of monitoring stations is in close proximity to the population center, particularly in more developed, eastern cities.

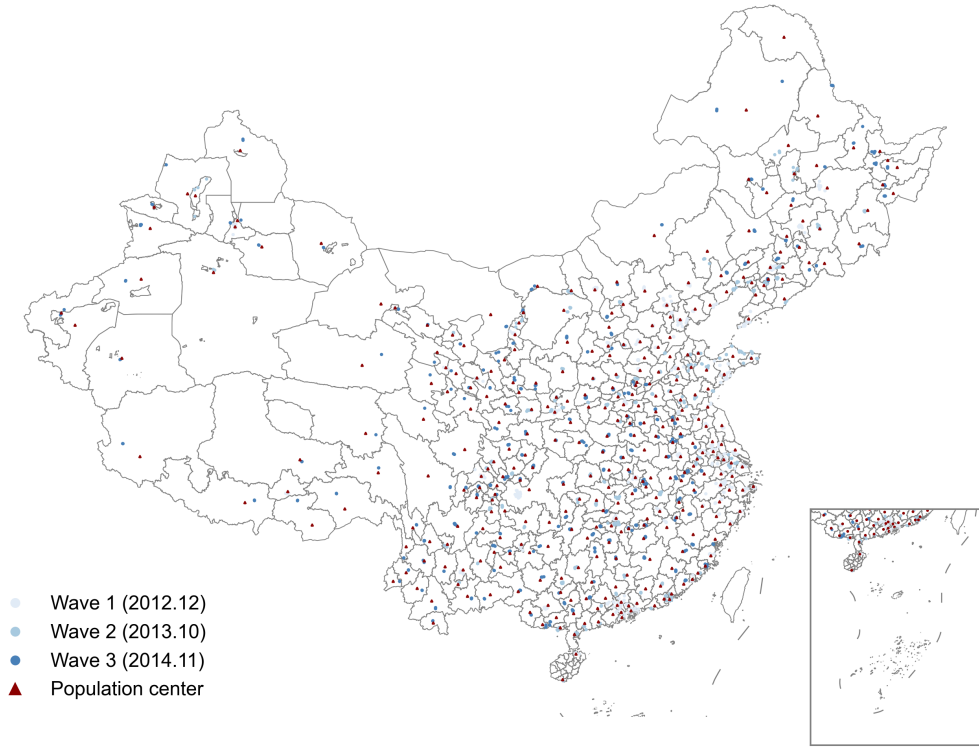


Figure A.2: Location of monitoring stations and city population centers

Notes: This figure illustrates the spatial distribution of the monitoring stations employed in this study and their corresponding city population centers. Each blue dot represents an individual monitoring station, while each red dot denotes the population center of a city. See Section A.5 for details regarding the calculation of population centers. In total, our research integrates data from 1,493 monitoring stations located across various prefecture-level administrative regions and municipalities.

A.3 Pollution data

We utilize satellite-derived $\text{PM}_{2.5}$ data from the Atmospheric Composition Analysis Group to measure location-specific air quality in China (Shen et al., 2024), accessible at <https://sites.wustl.edu>.

edu/acag/datasets/surface-pm2-5/. Our analyses primarily rely on their V6.GL.02.04 dataset, which provides global PM_{2.5} concentration estimates at a spatial resolution of up to $0.01^\circ \times 0.01^\circ$ from 1998 to 2023.

To estimate the land price elasticity with respect to pollution, we merge the pollution data with land transaction data. We first match each land parcel with its locating $0.01^\circ \times 0.01^\circ$ cell in the pollution data. Subsequently, we calculate the average PM_{2.5} concentration level for the three months corresponding to its transaction year-quarter. Consequently, the resulting land transaction dataset does not exhibit spatially even representativeness; instead, it assigns greater weight to locations with more transaction records, thereby reflecting the average pollution level encountered by land buyers.

In contrast, our cell-level pollution dataset, employed for investigating the pollution reduction effects of national monitoring, features evenly distributed observations. To this end, we construct a quarter-level panel based on their monthly dataset with a spatial resolution of $0.1^\circ \times 0.1^\circ$ cells. Figure A.3 illustrates a comparison between our parcel-level dataset and cell-level dataset.

A.4 Thermal inversion data

To mitigate potential endogeneity when estimating the causal effect of the national monitoring network on the pollution elasticity of land price, we construct an instrument for the pollution level based on the phenomenon of thermal inversion. Thermal inversion is a meteorological deviation from the typical atmospheric profile, where air temperature normally decreases with altitude. Under standard conditions, warm air near the ground ascends, facilitating the dispersion of pollutants into the upper atmosphere via convection. However, during an inversion episode, a layer of warmer air overlies a layer of cooler air near the surface, effectively creating a “lid” over a specific geographical area. This stable atmospheric stratification suppresses vertical mixing and traps airborne pollutants—such as particulate matter (PM_{2.5}, PM₁₀) and nitrogen oxides—close to the ground. Consequently, even when local emission levels remain constant, the concentration of pollutants within the inversion layer increases significantly, leading to acute episodes of severe air pollution.

To construct this measure, we utilize data from NASA’s MERRA-2 product M2I6NPANA, version 5.12.4, accessible at https://cmr.earthdata.nasa.gov/search/concepts/C1276812884-GES_DISC.html. This dataset provides air temperatures every 6 hours across 42 pressure levels, ranging from 1,000 hPa (approximately 110 m) to 0.1 hPa (approximately 65,000 m), with a spatial resolution of $0.625^\circ \times 0.5^\circ$. Following the methodology established by Arceo et al. (2016) and Fu et al. (2021), we define a thermal inversion as the condition where the temperature of the second-lowest atmospheric layer is higher than that of the lowest layer. For cells at high altitudes, such as those exceeding 1,000 m in Qinghai Province, temperature values for the first, second, or additional lower levels may be absent. In such instances, we utilize the two lowest available atmospheric layers with data. Given that there are four time points recorded within a day, we classify a day as a “thermal inversion day” if a thermal inversion occurs during any of these four observations. Subsequently, we define the proportion of thermal inversion days within a given quarter as a measure of thermal inversion intensity, which serves as an instrument for the quarterly pollution level.

The frequency and intensity of thermal inversions exhibit considerable heterogeneity across

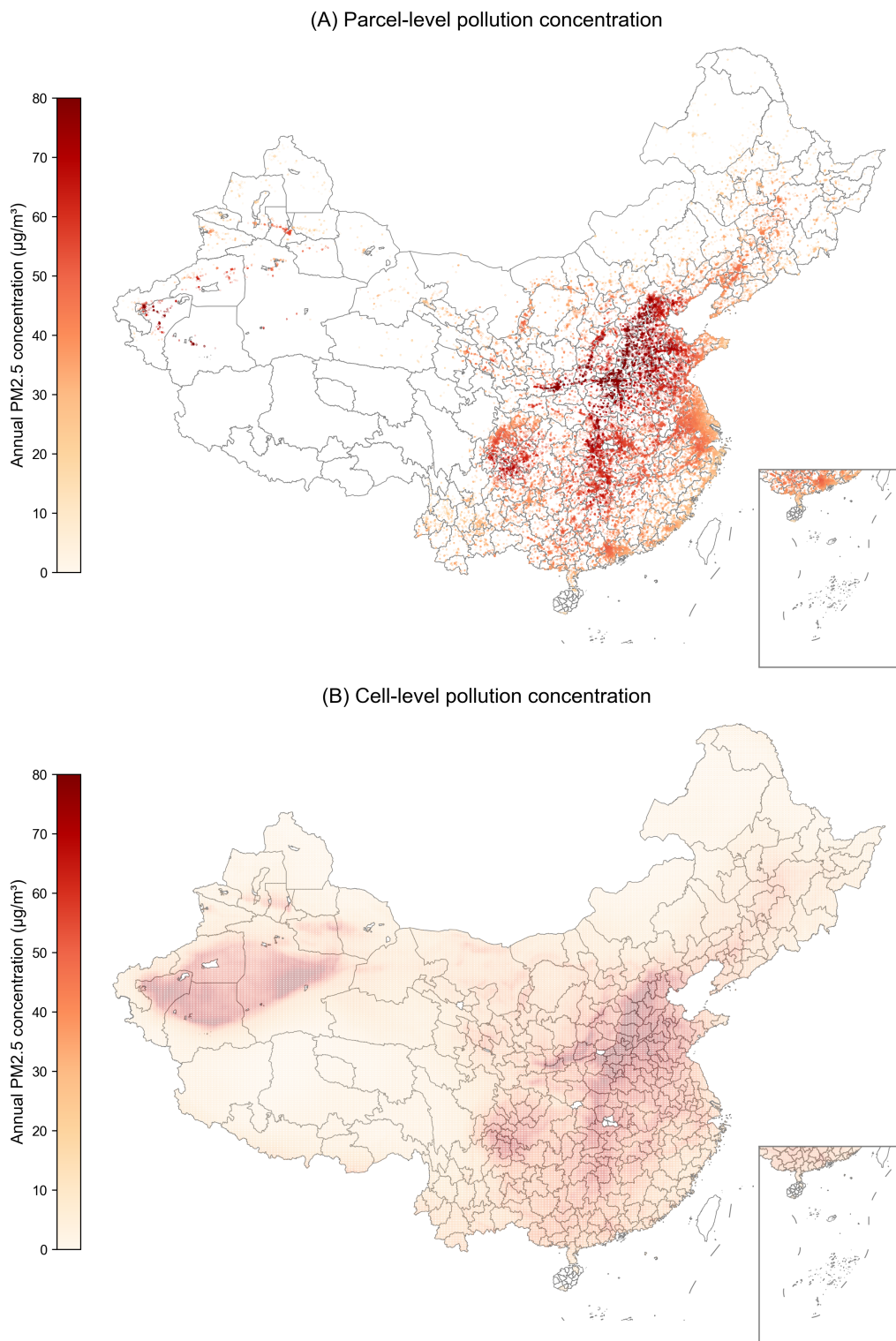


Figure A.3: Comparison between parcel-level pollution data and cell-level pollution data

Notes: This figure presents a comparison between parcel-level and cell-level pollution data, both depicting the annual PM_{2.5} concentration in 2012. The parcel-level data is constructed by first identifying land transaction records from 2012 and then matching these records with annual PM_{2.5} data with a spatial resolution of $0.01^\circ \times 0.01^\circ$. Conversely, the cell-level data is derived from monthly PM_{2.5} data with a $0.1^\circ \times 0.1^\circ$ resolution, by subsequently calculating the annual average.

China’s geography and seasons. Spatially, as shown in Figure A.4, thermal inversion is more prevalent in basin topographies and inland regions—such as the Chengdu Basin and parts of the North China Plain—where surrounding mountains impede air circulation, facilitating the accumulation of cold air near the surface. In contrast, coastal areas generally experience fewer severe inversion episodes due to the dynamic mixing effects of ocean breezes.

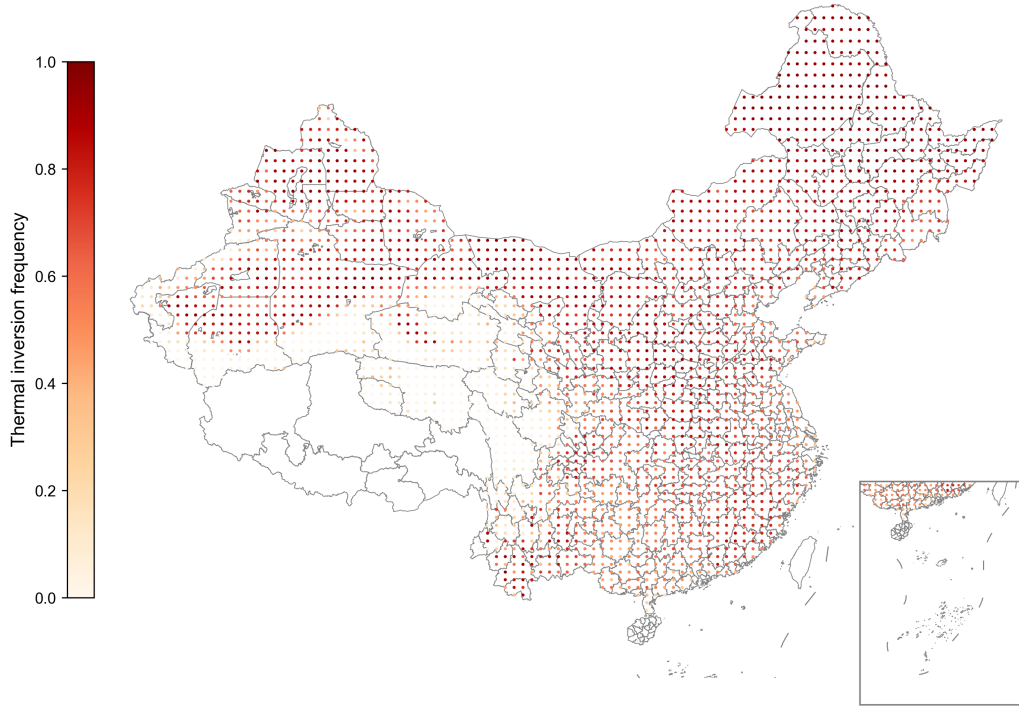


Figure A.4: Thermal inversion frequency during the first quarter of 2013

Notes: This figure illustrates the thermal inversion frequency during the first quarter of 2013, defined as the proportion of days experiencing thermal inversion. Each data point represents a cell from NASA’s data, with a spatial resolution of $0.625^\circ \times 0.5^\circ$. Only cells located within cities that have recorded land transactions in our dataset are presented in this figure.

Temporally, thermal inversion exhibits a notable seasonal pattern, with its frequency peaking during the autumn and winter months. This phenomenon is attributed to weaker solar radiation and extended nighttime periods, which collectively contribute to rapid radiative cooling of the ground and subsequent stabilization of the lower atmosphere. Conversely, summer months experience fewer inversion events due to enhanced convective instability driven by more intense surface heating. As depicted in Figure A.5, thermal inversion occurs significantly more frequently in the first and fourth quarters. Moreover, inter-year variation remains minimal.

A.5 Demographic data

We utilize demographic data to construct a crucial control variable in our analysis: the distance to the population center. This data is sourced from the Gridded Population of the World (GPWv4) dataset, specifically Version 4.11, provided by NASA. This dataset offers estimates of the number of population per cell, based on the 2010 national census, at a spatial resolution of $0.0083^\circ \times 0.0083^\circ$, publicly

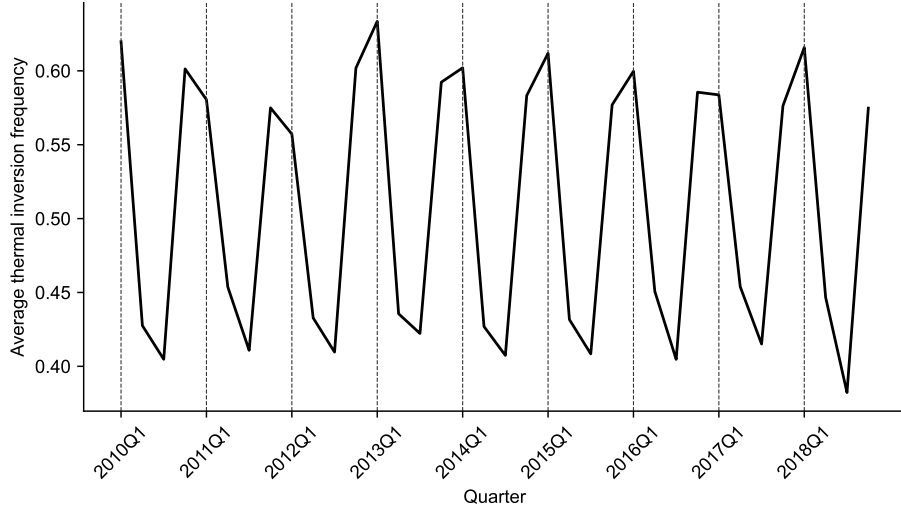


Figure A.5: Average thermal inversion frequency by year-quarter

Notes: This figure illustrates the average thermal inversion frequency by year-quarter. The calculation is based on cells located within cities that have recorded land transactions in our dataset.

available at <https://www.earthdata.nasa.gov/data/catalog/sedac-ciesin-sedac-gpww4-apct-wpp-2011>.

The location of each city’s population center is calculated as follows:

$$(x_c, y_c) = \frac{\sum_{g \in \mathcal{G}_c} \text{Population}_g \cdot (x_g, y_g)}{\sum_{g \in \mathcal{G}_c} \text{Population}_g},$$

where $\mathcal{G}_c$ represents the set of all grid cells within city c , Population_g denotes the population count in cell $g \in \mathcal{G}_c$, and (x_g, y_g) corresponds to its longitude and latitude coordinates. Consequently, the coordinates of city c ’s population center, (x_c, y_c) , is effectively a “center of mass” weighted by population count. Population centers of cities in the three-wave national rollout are presented in Figure A.2.

As a sanity check, Figure A.6 illustrates the relationship between a land parcel’s distance to its corresponding city population center and its unit price, separately for industrial and residential land. This relationship is conditional on a set of land attributes, city fixed effects, and year-quarter fixed effects. Consistent with existing literature, our data indicate that land parcels located closer to the city center are, on average, more expensive. Both land types demonstrate a good fit to a linear specification. Additionally, we observe that the estimated slope, typically defined as the price gradient with respect to distance to the city center, is steeper for residential land. This phenomenon can be attributed to the intense competition for investments among local governments, which often results in very low unit prices for industrial land, even for parcels situated near the city center. As depicted in the figure, when the distance residuals are below -0.5 , the average unit price of industrial land remains almost constant.

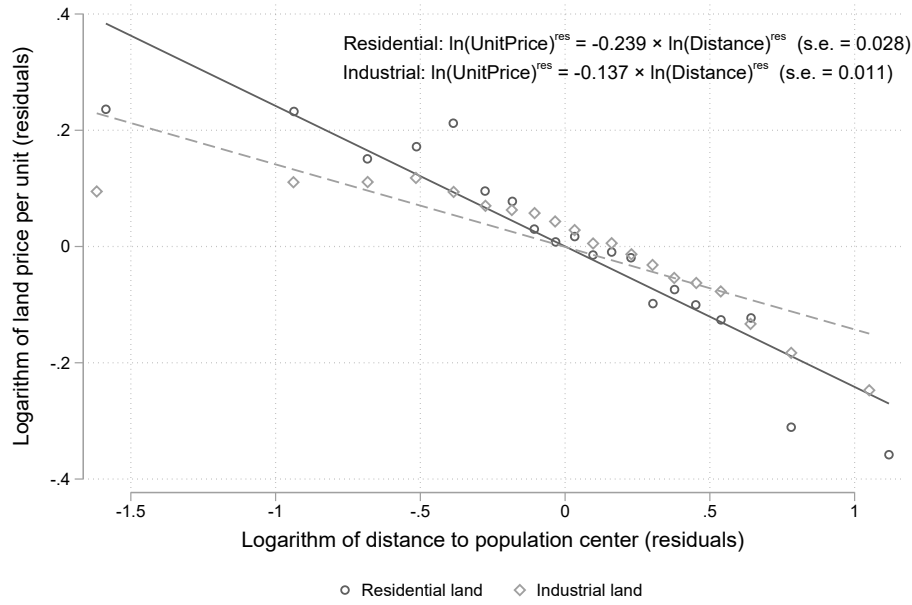


Figure A.6: Distance to city population center versus land price

Notes: This figure presents binscatter plots illustrating the relationship between a land parcel's distance to the city's population center and its unit land price. The estimations control for city fixed effects, year-quarter fixed effects, and a set of land attributes, including the parcel's rank, source, transaction mechanism, and the industry of the buyer. Residential (and commercial) land and industrial land are estimated and plotted separately.

A.6 City leader characteristics data

We quantify the promotion incentive for each city leader using characteristics of party secretaries (*shiweishuji*) in 2012. These characteristics include their age at assuming office, initial hierarchical level, educational background, and experience within the central government. All this information is sourced from the Chinese Political Elite Database (CPED), developed by Jiang (2018) and accessible at <https://www.junyanjiang.com/data.html>. This dataset contains fundamental information for each prefectural-level party secretary, such as birth dates, which enable the calculation of their age upon assuming power. Crucially, it also delineates the complete career trajectory of each leader up to 2015, encompassing their hierarchical and educational levels at various stages.

Another variable of interest is whether these leaders received a promotion subsequent to their tenure as party secretary. To ascertain this, we compare the hierarchical level held during their party secretary stage with the level attained in their next political appointment. An elevation in hierarchical level in the subsequent stage indicates a promotion. Given that the CPED dataset records information prior to 2015, we were initially able to determine the hierarchical level in the subsequent political stage for only 29 out of the 74 party secretaries in Wave 1 cities. We then augmented this data with 7 additional values obtained from the replication data of Wang et al. (2020), accessible at <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/N3TUEA>. The remaining 38 missing values were subsequently collected manually from pertinent news articles and online reports.

With a similar dataset for party secretaries spanning from 2000 to 2011, Wang et al. (2020)

estimate a baseline probit model to predict a city leader's promotion likelihood as a function of their initial age and hierarchical rank at the commencement of office, along with their interaction term. Specifically, the estimated coefficients presented in Column (3) of their Table 2 yield the following promotion likelihood function:

$$\begin{aligned}\hat{L}_n^{\text{baseline}} = & \Phi^{-1}(6.368 - 0.136 \times \text{StartAge}_n - 7.935 \times \mathbf{1}\{\text{StartLevel}_n = \text{Deputy-province}\} \\ & - 1.547 \times \mathbf{1}\{\text{StartLevel}_n = \text{Province or above}\} \\ & + 0.136 \times \text{StartAge}_n \times \mathbf{1}\{\text{StartLevel}_n = \text{Deputy-province}\} \\ & + 0.060 \times \text{StartAge}_n \times \mathbf{1}\{\text{StartLevel}_n = \text{Province or above}\}),\end{aligned}$$

where $\Phi^{-1}(\cdot)$ denotes the inverse cumulative distribution function of the standard normal distribution, and StartAge_n and StartLevel_n represent leader n 's initial age and hierarchical rank at the commencement of their office, respectively. The discrete variable StartLevel_n can assume one of three values: prefectural level, deputy-province level, or province or above level. Based on this prediction function, we derive our baseline measure for political promotion incentives.

Additionally, Wang et al. (2020) estimate an extended model that further incorporates two dummy variables indicating whether a city leader previously worked in the central government and possessed a graduate degree. In Column (4) of their Table 2, an extended prediction function for promotion likelihood is given by

$$\begin{aligned}\hat{L}_n^{\text{extended}} = & \Phi^{-1}(5.858 - 0.128 \times \text{StartAge}_n - 8.524 \times \mathbf{1}\{\text{StartLevel}_n = \text{Deputy-province}\} \\ & - 1.279 \times \mathbf{1}\{\text{StartLevel}_n = \text{Province or above}\} \\ & + 0.146 \times \text{StartAge}_n \times \mathbf{1}\{\text{StartLevel}_n = \text{Deputy-province}\} \\ & + 0.051 \times \text{StartAge}_n \times \mathbf{1}\{\text{StartLevel}_n = \text{Province or above}\} \\ & + 0.672 \times \text{CentralExp}_n + 0.198 \times \text{Graduate}_n),\end{aligned}$$

where CentralExp_n takes the value of 1 if leader n previously worked in the central government, and Graduate_n takes the value of 1 if leader n possessed a graduate degree in 2012. Utilizing this prediction function, we derive our extended measure for political promotion incentives.

A.7 Other data sources

We utilize prefecture-level variables, including each city's annual GDP and resident population, when matching land parcels in Wave 1 cities to parcels in other cities with similar attributes. These data, spanning from 2010 to 2018, are sourced from the annual *China City Statistical Yearbook*. Additionally, we construct a measure to reflect each city's emphasis on environmental protection, drawing from government reports published in 2011. To this end, these texts were manually extracted from the official website of each city.

Our prefecture-level Geographic Information System polygon map is obtained from the National Platform for Common GeoSpatial Information Services, administered by China's Ministry of Natural Resources, and is accessible via <https://cloudcenter.tianditu.cn/administrativeDivision>.

B Monte Carlo simulation on estimator consistency

This appendix details a set of Monte Carlo simulations designed to address three key questions pertinent to our identification strategy in Section 5:

1. Is the estimated coefficient for the triple-interaction term in Equation (11) consistent when monitoring affects the pollution level?
2. What is the direction of bias if the effects of monitoring on pollution levels are heterogeneous?
3. Can the triple-interaction term coefficient be consistently estimated when an instrumental variable for pollution levels is employed?

We begin by specifying the following data generating process (DGP). Suppose there are 80,000 residential land parcels evenly distributed across 200 cities, denoted by $c \in \{1, \dots, 200\}$, and 8 periods, denoted by $t \in \{1, \dots, 8\}$. Within each simulation run, we employ a random procedure to select approximately half of the 200 cities to serve as treatment cities (i.e., Wave 1 cities in our empirical analysis), and subsequently assume these cities are exposed to the treatment beginning in the fifth period. The DGP is structured as follows:

$$\begin{aligned}
 \ln Pollution_{i,t} &= -0.5 \times \mathbf{1}\{\text{Wave 1}\}_{c(i)} \times After_t + 2 \times \mathbf{1}\{\text{Wave 1}\}_{c(i)} - 0.1 \times t + z_{i,t} + u_{i,t} + e_{i,t}^1, \\
 \ln UnitPrice_{i,t} &= -0.2 \times \ln Pollution_{i,t} \times \mathbf{1}\{\text{Wave 1}\}_{c(i)} \times After_t + 5 \times \mathbf{1}\{\text{Wave 1}\}_{c(i)} \\
 &\quad - 0.5 \times \ln Pollution_{i,t} + t + u_{i,t} + e_{i,t}^2, \\
 z_{i,t} &\sim \text{i.i.d. } \mathcal{N}(0, 1), \\
 u_{i,t} &\sim \text{i.i.d. } \mathcal{N}(0, 1), \\
 e_{i,t}^1 &\sim \text{i.i.d. } \mathcal{N}(0, 1), \\
 e_{i,t}^2 &\sim \text{i.i.d. } \mathcal{N}(0, 1).
 \end{aligned} \tag{B.1}$$

Crucially, in the generation of $\ln Pollution_{i,t}$, we assume that the treatment (i.e., national monitoring) exerts a homogeneous, one-time effect on the pollution level, decreasing it by 0.5 units. Should this effect be null, then conditionally on other variables, the treatment status, $\mathbf{1}\{\text{Wave 1}\}_{c(i)} \times After_t$, would be independent of $\ln Pollution_{i,t}$. As demonstrated by Barwick et al. (2024), the estimate for the triple-interaction term in the land price equation is consistent under such conditions. Our objective here is to investigate whether the estimate remains consistent in the presence of such an effect.

Moreover, given that Wave 1 cities are typically more developed and consequently more polluted, we assign a higher initial pollution level to them, as represented by the term $2 \times \mathbf{1}\{\text{Wave 1}\}_{c(i)}$. A linear time trend, $-0.1 \times t$, is also included to capture the gradual improvement of air quality. Furthermore, we assume the existence of an instrumental variable for pollution, $z_{i,t}$, which is independently drawn from a standard normal distribution. By construction, $z_{i,t}$ acts as a determinant of pollution (*relevance*), is excluded from the structural equation of land price (*exogeneity*), and influences land price exclusively through its effect on pollution (*exclusion restriction*). Thus, it constitutes a valid

instrument. Its role in mitigating potential estimation bias will be discussed subsequently. Unobserved confounding factors (e.g., amenities), denoted by $u_{i,t}$, are present in the structural equations for both pollution and land price, thereby inducing endogeneity in $\ln Pollution_{i,t}$. For instance, enhanced proximity to transportation infrastructure may exhibit a positive correlation with elevated pollution levels, while concurrently leading to higher housing and, consequently, residential land prices. Finally, $e_{i,t}^1$ represents an idiosyncratic error term.

For the generation of $\ln UnitPrice_{i,t}$, we posit that the treatment decreases the pollution elasticity of residential land price by 0.2, with the baseline pollution elasticity set at -0.5 , a value consistent with the estimates presented in our main text. Furthermore, Wave 1 cities are assumed to have higher initial land prices, captured by the term $5 \times \mathbf{1}\{\text{Wave } 1\}_{c(i)}$, alongside a uniform linear increasing time trend for land prices. Finally, $u_{i,t}$ represents the omitted variable, and $e_{i,t}^2$ denotes an idiosyncratic error term. Consequently, within this DGP, the treatment exclusively influences residential land prices through two channels: (i) its effect on pollution levels and (ii) its effects on the pollution elasticity of land price.

Using the simulated data, we estimate the following regression equation:

$$\begin{aligned} \ln UnitPrice_{i,t} = & c_0 + \phi \cdot \ln Pollution_{i,t} \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times After_{i,t} + c_1 \cdot \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times After_t \\ & + c_2 \cdot \ln Pollution_{i,t} + \delta_{c(i)} + \nu_t + \epsilon_{i,t}, \end{aligned} \quad (\text{B.2})$$

where $\delta_{c(i)}$ represents city fixed effects and ν_t represents time fixed effects. This specification is a simplified variant of the full Triple-Differences model employed in Columns (3) and (5) of Table 1. In Equation (B.2), we intentionally omit the interaction terms between pollution and city fixed effects, as well as those between pollution and time fixed effects. This simplification is justified because our DGP assumes a constant baseline pollution elasticity across both cities and time periods in the absence of treatment intervention. We confirm that our simulation results remain robust even if these additional sources of heterogeneity are incorporated.

For each specified DGP, we generate 500 simulation samples, estimate Equation (B.2) using each sample, and record the estimated coefficients for both the triple-interaction term and the pollution variable. Figure B.1 presents the kernel density estimate of these 500 coefficients. As anticipated, the endogeneity of $\ln Pollution_{i,t}$ leads to a significant divergence between the estimated coefficients and the true causal parameter. As depicted in Panel A, the mean of these 500 estimated coefficients is -0.167 , which constitutes a notable overestimation compared to the true causal coefficient of -0.5 . This discrepancy elucidates why positive point estimates for pollution are often observed in the regressions in the main text. Conversely, Panel B demonstrates a consistent point estimate for the triple-interaction term: both the mean of the 500 estimated coefficients and the true coefficient are -0.2 . This indicates that even when the assumption of conditional independence between pollution and the treatment indicator is not satisfied, consistent estimates can still be obtained if the treatment effect is a homogeneous, one-time event. This finding further substantiates the argument by Barwick et al. (2024) that this conditional independence assumption serves as a *sufficient* condition for consistency.

The subsequent question is: If the treatment effects on pollution are not a homogeneous, one-

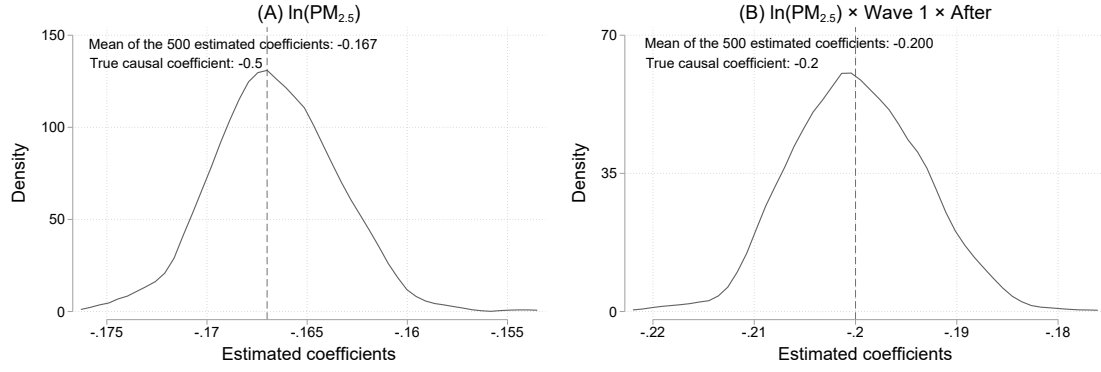


Figure B.1: Monte Carlo simulation for a homogeneous, one-time treatment effect

Notes: This figure presents the kernel density distributions of the estimated coefficients for $\ln Pollution_{i,t}$ (Panel A) and $\ln Pollution_{i,t} \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times After_{i,t}$ (Panel B), derived from 500 simulation samples. These samples were generated according to the data generating process specified in Equation (B.1). The dashed line indicates the mean of these 500 estimated coefficients, which is explicitly marked in the figure along with the true causal coefficient.

time event but rather exhibit heterogeneity, is the point estimate still consistent? To investigate this, we modify the previously defined DGP by positing that air quality improvement exhibits a linear relationship with proximity to monitoring stations within treatment cities. This revised DGP is specified as:

$$\begin{aligned}
 \ln Pollution_{i,t} &= -0.02 \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times After_t \times (50 - Distance_i^{\text{monitor}}) + 2 \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \\
 &\quad - 0.1 \times t + z_{i,t} + u_{i,t} + e_{i,t}^1, \\
 \ln UnitPrice_{i,t} &= -0.2 \times \ln Pollution_{i,t} \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times After_t + 5 \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \\
 &\quad - 0.5 \times \ln Pollution_{i,t} + t + u_{i,t} + e_{i,t}^2, \\
 z_{i,t} &\sim \text{i.i.d. } \mathcal{N}(0, 1), \\
 u_{i,t} &\sim \text{i.i.d. } \mathcal{N}(0, 1), \\
 e_{i,t}^1 &\sim \text{i.i.d. } \mathcal{N}(0, 1), \\
 e_{i,t}^2 &\sim \text{i.i.d. } \mathcal{N}(0, 1).
 \end{aligned} \tag{B.3}$$

The primary distinction of this DGP resides in the first term of the $\ln Pollution_{i,t}$ equation. This term is now multiplied by $(50 - Distance_i^{\text{monitor}})$, resulting in $-0.02 \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times After_t \times (50 - Distance_i^{\text{monitor}})$. Here, $Distance_i^{\text{monitor}}$ represents a random draw of the distance to the nearest monitoring station for each land parcel, sampled independently from a uniform distribution $\mathcal{U}[0, 50]$.

Following the previous methodology, we construct 500 simulation samples and estimate Equation (B.2) for each. The kernel density distribution of these estimates is presented in Figure B.2. This time, the mean of the 500 estimated coefficients for the triple-interaction term is found to be -0.209 . While this value is numerically close to the preset causal parameter of -0.2 , it nonetheless indicates inconsistency. This finding implies that the consistency observed in Panel B of Figure B.1 is predicated upon a specific and potentially restrictive assumption. Should the treatment effects on pollution exhibit spatial heterogeneity—a plausible scenario in our empirical context—the OLS

estimator specified in Equation (B.2) can no longer ensure consistent estimation.

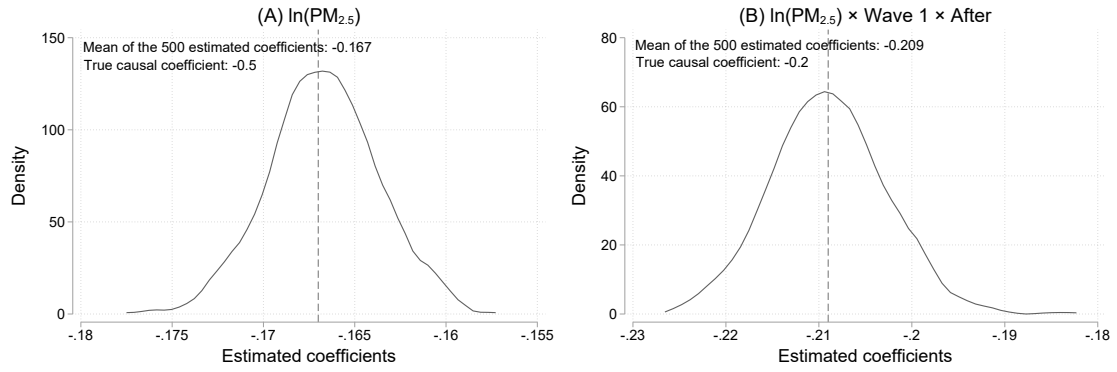


Figure B.2: Monte Carlo simulation for heterogeneous treatment effects

Notes: This figure presents the kernel density distributions of the estimated coefficients for $\ln \text{Pollution}_{i,t}$ (Panel A) and $\ln \text{Pollution}_{i,t} \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times \text{After}_{i,t}$ (Panel B), derived from 500 simulation samples. These samples were generated according to the data generating process specified in Equation (B.3). The dashed line indicates the mean of these 500 estimated coefficients, which is explicitly marked in the figure along with the true causal coefficient.

In a separate, unreported simulation exercise, we investigated whether inter-temporal heterogeneous treatment effects also introduce bias into the estimation. For this, we posited a linearly strengthening treatment effect over time across all treatment cities, while maintaining homogeneity in spatial effects. For instance, the pollution level in treated cities was modeled to decrease by 0.5 units in period 5, 1 unit in period 6, 1.5 units in period 7, and 2 units in period 8. Under such a scenario, we again observed that the estimate for the triple-interaction term exhibited inconsistency.

Fortunately, the availability of a valid instrumental variable for pollution enables the achievement of consistent estimates. As previously discussed, we designed the variable $z_{i,t}$ within our DGP to satisfy all requisite assumptions for a valid instrument. Consequently, we employ $z_{i,t}$ as the instrumental variable for $\ln \text{Pollution}_{i,t}$, and $z_{i,t} \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times \text{After}_{i,t}$ as the instrument for $\ln \text{Pollution}_{i,t} \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times \text{After}_{i,t}$. The model is then estimated using the Two-Stage Least Squares estimator. The estimates derived from the 2SLS estimator are presented in Figure B.3. In this instance, we observe that the estimates for both $\ln \text{Pollution}_{i,t}$ and the triple-interaction term are consistent.

In conclusion, our simulations address the three questions posed at the outset. The estimated coefficient for the focal triple-interaction term in Equation (11) remains consistent even when monitoring directly influences pollution levels, contingent upon the treatment effect on pollution being a homogeneous, one-time event. However, when the effects of monitoring on pollution levels exhibit spatial or inter-temporal heterogeneity, the OLS estimator for the triple-interaction term is demonstrated to be inconsistent. Nonetheless, by utilizing instruments for pollution (and its interactions), consistent estimates for both the triple-interaction term and the direct effect of pollution can be re-obtained, even in the presence of heterogeneous treatment effects on pollution.

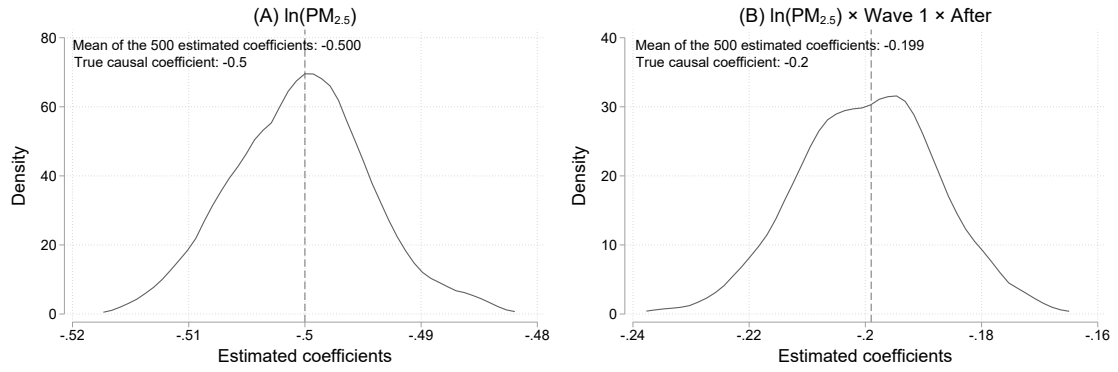


Figure B.3: Monte Carlo simulation for heterogeneous treatment effects with IV estimator

Notes: This figure displays the kernel density distributions of the estimated coefficients for $\ln Pollution_{i,t}$ (Panel A) and $\ln Pollution_{i,t} \times \mathbf{1}\{\text{Wave 1}\}_{C(i)} \times After_{i,t}$ (Panel B) obtained from 500 simulation samples. These coefficients are derived from an IV estimator designed to mitigate endogeneity bias. The samples were generated according to the data generating process specified in Equation (B.3). The dashed line indicates the mean of these 500 estimated coefficients, which is explicitly marked in the figure along with the true causal coefficient.

C Immediate treatment effects of monitoring on air quality

This appendix presents estimates of the immediate treatment effects of the national monitoring network on PM_{2.5} concentrations. As discussed in Section B, reductions in pollution levels in treated cities attributable to monitoring, particularly when treatment effects exhibit spatial or inter-temporal heterogeneity, could introduce estimation bias into our focal coefficient. Motivated by this econometric concern, and given that our primary analyses in the main text focus primarily on the four quarters following the first-wave monitoring, our investigation is therefore confined to the immediate effects on pollution, in contrast to existing studies that estimate average treatment effects over multi-year horizons.

To estimate this effect, we employ two distinct datasets: one at the cell level and another at the land parcel level. First, a cell-level panel dataset is constructed (as detailed in Section A.3), documenting the quarterly average PM_{2.5} concentration for each cell with a spatial resolution of $0.1^\circ \times 0.1^\circ$. With this dataset, we estimate the following two-way fixed effects difference-in-differences specification:

$$\ln Pollution_{g,t} = \beta_0 + \beta_1 \cdot \mathbf{1}\{\text{Wave 1}\}_{c(g)} \times After_t + \delta_{c(g)} + \nu_t + \varsigma_{p(g),t} + \epsilon_{g,t}, \quad (\text{C.1})$$

where $Pollution_{gt}$ represents the average PM_{2.5} concentration in cell g during year-quarter t . The indicator variable $\mathbf{1}\{\text{Wave 1}\}_{c(g)}$ equals 1 if cell g is located in one of the Wave 1 cities, and $After_t$ is an indicator equal to 1 for 2012Q4 and subsequent quarters. Furthermore, $\delta_{c(g)}$ denotes city fixed effects, ν_t represents year-quarter fixed effects, and ϵ_{gt} is the error term. In some specifications, we further incorporate province-year-quarter fixed effects, $\varsigma_{p(g),t}$, to absorb province-specific time-varying trends. Within this specification, the parameter β_1 captures the treatment effect on the pollution level.

Observations from 2010Q4 to 2013Q3 are utilized to estimate Equation (C.1), with the results presented in Table C.1. Columns (1) and (2) present estimates derived by comparing Wave 1 cities with Wave 2 and Wave 3 cities. Column (3) excludes cells located in Wave 2 cities as a robustness check, addressing potential concerns stemming from the premature installation of monitoring stations in a subset of Wave 2 cities. Column (4) limits the estimation sample to cells located within 50 kilometers of their respective city population centers, with the aim of focusing on treatment effects within central urban areas, which typically exhibit higher pollution levels. Columns (5) and (6) further divide our sample into two distinct groups: cells within a 3-kilometer radius of any monitoring stations in their corresponding cities, and those located beyond this range. The former group represents areas where local governments may have a stronger incentive to reduce pollutant concentrations.

Across all specifications presented in these columns, we observe that the point estimates for the DD interaction term remain small in magnitude and statistically insignificant. This suggests that automated monitoring does not substantially alter pollution levels within a relatively short period of four quarters. This finding is consistent with the observations of Yang et al. (2024), who similarly estimated a marginal average effect across entire cities. Nevertheless, the consistently positive sign

of the point estimates is counter-intuitive, implying the potential existence of uncaptured pre-trends in our quarterly pollution data, especially given its discernible seasonal variations.

Table C.1: Estimating treatment effects of monitoring on the pollution level with cell-level data

	Dependent variable: Logarithm of PM _{2.5} concentration					
	(1)	(2)	Wave 1 vs. Wave 3	Dist. pop. center	Dist. nearest monitor	
				≤ 50 km	≤ 3 km	> 3 km
			(3)	(4)	(5)	(6)
Wave 1 × After	0.003 (0.017)	0.030 (0.022)	0.041 (0.027)	0.017 (0.010)	0.017 (0.010)	0.030 (0.023)
City FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year–quarter FEs	Yes	No	No	No	No	No
Province–yq FEs	No	Yes	Yes	Yes	Yes	Yes
# of clusters	335	335	248	335	214	335
# of observations	1,144,404	1,144,404	939,648	244,884	3,612	1,140,780

Notes: This table presents the estimated immediate treatment effects of automatic monitoring on PM_{2.5} concentration, derived from the estimation of Equation (C.1). The estimation sample consists of cell-level panel data with a spatial resolution of $0.1^\circ \times 0.1^\circ$. In all columns, cells situated in Wave 1 cities serve as the treatment group, while cells in Wave 2 and Wave 3 cities comprise the control group. An exception is Column (3), where cells in Wave 2 cities are excluded for robustness checking. Column (4) restricts the estimation sample to cells located within 50 kilometers of their respective city population centers. Columns (5) and (6) further divide the sample into two distinct groups: cells within a 3-kilometer radius of any monitoring station in their corresponding cities, and those situated beyond this range. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As an alternative, we utilize the parcel-level dataset to re-estimate the immediate pollution reduction effects of monitoring. In contrast to the spatially uniform cell-level data, the parcel-level dataset exclusively covers cells with recorded land transactions and assigns higher weights to areas with substantial transaction volumes. Consequently, the ensuing estimates reflect the treatment effects on pollution levels experienced by land buyers. To directly assess the independence of the treatment indicator from the pollution level, conditional on other variables, we estimate the following specification, analogous to that employed in the main text:

$$\ln Pollution_{i,t} = \beta_0 + \beta_1 \cdot \mathbf{1}\{\text{Wave 1}\}_{c(i)} \times After_t + \delta_{c(i)} + \nu_t + \mathbf{X}'_i \beta + \epsilon_{i,t}, \quad (\text{C.2})$$

where parcel-specific attributes, city fixed effects, and year–quarter fixed effects are incorporated into the estimation.

Estimation results are provided in Table C.2. Estimations are conducted using both the full sample and the two distinct matching samples described in the main text. Across all specifications and samples, we once again find all point estimates to be positive, with some achieving statistical significance. To address concerns regarding uncaptured pre-trends in pollution levels, existing studies commonly assume spatial heterogeneity in treatment effects. This heterogeneity is then leveraged to construct an additional dimension of “difference” to account for these pre-trends. For example,

Xie and Yuan (2023) introduce a comparison between upwind areas and other areas within a city, revealing that local governments strategically reduce pollution more effectively in upwind regions. More pertinent to our study's focus on strategic behavior based on proximity to monitoring stations, Yang et al. (2024) utilize a comparison between grid cells within a 3-kilometer radius of a monitor and those located further away.

Columns (3) to (5) present a preliminary investigation into such spatial heterogeneity. Specifically, when employing our constructed matching samples, which offer greater comparability than the full sample, the estimates reported in Columns (3) and (4) are small in magnitude and statistically insignificant. This observation is particularly pronounced when contrasted with the effects observed for parcels situated beyond a 3-kilometer radius from any monitoring stations in their respective cities. This suggests that, in the short term, local governments may strategically concentrate their regulatory enforcement efforts in city centers and areas in close proximity to monitoring stations to mitigate further pollution increases, concurrently relaxing enforcement in regions more remote from these monitors. This finding aligns with the results presented in Yang et al. (2024), which elucidate similar strategic behaviors contingent upon proximity to monitoring stations.

Inspired by these findings, we similarly estimate the following Triple-Differences specification:

$$\begin{aligned} \ln Pollution_{i,t} = & \gamma_0 + \gamma_1 \cdot \mathbf{1}\{\text{Wave 1}\}_{c(i)} \times After_t \times Near_i + \gamma_2 \cdot \mathbf{1}\{\text{Wave 1}\}_{c(i)} \times After_t \\ & + Near_i \times \delta_{c(i)} + Near_i \times \nu_t + \mathbf{X}'_i \boldsymbol{\beta} + \epsilon_{i,t}, \end{aligned} \quad (\text{C.3})$$

where $Near_i$ is a distance indicator variable equal to 1 if parcel i is located within a 3-kilometer radius of any monitoring station in its corresponding city, and 0 otherwise.

Estimation results are reported in Table C.3. We derive consistent point estimates of approximately -0.024 for the triple-differences term in both columns. Although the estimate in Column (1) does not achieve statistical significance, its numerical value is consistent with that in Column (2), and its non-significance is primarily attributable to a higher standard error, likely resulting from the smaller sample size, rather than indicating an absence of the underlying effect. The magnitude of these estimates is comparable to those reported in Yang et al. (2024).

In conclusion, the estimates presented in this Appendix suggest that monitoring may not exert a significant pollution reduction effect across the entire city. However, we find evidence consistent with existing literature, underscoring the spatial heterogeneity of this effect. When considered in conjunction with the simulation results detailed in Appendix B, these findings indicate the necessity of employing an instrumental variable for pollution levels to robustly validate the estimates derived from the OLS estimator.

Table C.2: Estimating treatment effects of monitoring on the pollution level with the parcel-level data

	Dependent variable: Logarithm of PM _{2.5} concentration				
		Wave 1 vs. Wave 3	Dist. pop. center	Dist. nearest monitor	
			≤ 50 km	≤ 3 km	> 3 km
	(1)	(2)	(3)	(4)	(5)
<i>Panel A. Full sample</i>					
Wave 1 × After	0.040*** (0.012)	0.050*** (0.013)	0.038*** (0.014)	0.036*** (0.014)	0.040*** (0.013)
# of clusters	327	240	324	326	327
# of observations	508,241	364,626	345,464	95,983	412,256
<i>Panel B. Two-step matching</i>					
Wave 1 × After	0.021 (0.015)	0.028* (0.016)	0.013 (0.016)	0.000 (0.017)	0.025 (0.016)
# of clusters	286	200	286	285	285
# of observations	229,178	179,212	173,422	45,453	183,713
<i>Panel C. Mahalanobis matching</i>					
Wave 1 × After	0.030** (0.014)	0.047*** (0.013)	0.024 (0.015)	0.010 (0.016)	0.035** (0.014)
# of clusters	286	200	286	286	286
# of observations	292,853	249,141	220,561	56,156	236,694
Controls	Yes	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes	Yes
Year–quarter fixed effects	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the estimated immediate treatment effects of automatic monitoring on PM_{2.5} concentration, derived from the estimation of Equation (C.2). The estimation sample consists of parcel-level data. Each observation is a land transaction records, with the pollution level of its locating 0.01° × 0.01° cell. In all columns, parcels situated in Wave 1 cities serve as the treatment group, while parcels in Wave 2 and Wave 3 cities comprise the control group. An exception is Column (2), where parcels in Wave 2 cities are excluded for robustness checking. Column (3) restricts the estimation sample to parcels located within 50 kilometers of their respective city population centers. Columns (4) and (5) further divide the sample into two distinct groups: parcels within a 3-kilometer radius of any monitoring station in their corresponding cities, and those situated beyond this range. Panel A uses the full land parcel transaction dataset, while Panels B and C utilize samples constructed via two distinct matching procedures described in the main text. Standard errors, clustered at the city level, are reported in parentheses.

*** p < 0.01, ** p < 0.05, * p < 0.1.

Table C.3: Treatment effects of monitoring on pollution levels of parcels near monitoring stations

	Dependent variable: Logarithm of unit price of land parcel	
	Two-step matching	Mahalanobis matching
	(1)	(2)
Wave 1 $\times$ After $\times$ Near	−0.023 (0.017)	−0.024** (0.012)
Wave 1 $\times$ After	0.025 (0.016)	0.035** (0.014)
Controls	Yes	Yes
Year–quarter fixed effects $\times$ Near	Yes	Yes
City fixed effects $\times$ Near	Yes	Yes
# of clusters	286	286
# of observations	229,177	292,852

Notes: This table reports the treatment effects of monitoring on pollution levels of parcels near monitoring stations by estimating Equation (C.3). Samples constructed via two distinct matching procedures described in the main text are utilized. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

D Alternative methods for estimating the difference in counterfactual pollution levels

D.1 Using residential parcels as controls

In Section 6.2, we adopt the assumption of negligible pollution increases attributable to residential land parcels to facilitate the construction of a more comparable control group for industrial parcels. While the difference $\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}$ could alternatively be quantified by directly matching industrial parcels with residential parcels, this method would face considerable challenges in identifying perfectly comparable residential parcels for a large proportion of industrial parcels. In this section, we detail the underlying econometric rationale and our alternative matching procedure employing residential parcels.

For enhanced clarity, we denote parcels transacted for industrial use as i_I and those for residential use as i_R . Drawing upon Equation (12), consider an ideal scenario where we identify a residential land parcel i_R that possesses identical land attributes and initial pollution levels as an industrial land parcel i_I . Such a parcel i_R would constitute a perfectly comparable control group. In this context, the observed difference in pollution levels can be expressed as:

$$\ln Pollution_{g(i_I),\tau}^{\text{obs}} - \ln Pollution_{g(i_R),\tau}^{\text{obs}} = \ln Pollution'_{i_I,I,t} - \ln Pollution'_{i_R,R,t} + \epsilon_{g(i_I),\tau} - \epsilon_{g(i_R),\tau}. \quad (\text{D.1})$$

Given that parcels i_I and i_R share identical land attributes (i.e., $M_{i_I,t} = M_{i_R,t}$), their counterfactual pollution differences should be equivalent, satisfying:

$$\ln Pollution'_{i_I,I,t} - \ln Pollution'_{i_R,R,t} = \ln Pollution'_{i_I,I,t} - \ln Pollution'_{i_R,R,t} = M'_{i_I,t} \rho. \quad (\text{D.2})$$

As established in the theoretical framework, the coefficient vector ρ is interpreted as the difference in coefficients between the pollution level functions for industrial and residential land uses. More precisely,

$$\ln \left(\frac{Pollution'_{i_I,I,t}}{Pollution_{i_I,t}} \right) = M'_{i_I,t} \rho^I \quad (\text{D.3})$$

and

$$\ln \left(\frac{Pollution'_{i_I,R,t}}{Pollution_{i_I,t}} \right) = M'_{i_I,t} \rho^R. \quad (\text{D.4})$$

The difference between Equations (D.3) and (D.4) directly yields Equation (D.2), where $\rho \equiv \rho^I - \rho^R$. Similar relationship holds for i_R . Consequently, we have:

$$\ln Pollution'_{i_I,I,t} = \ln Pollution_{i_I,t} + M'_{i_I,t} \rho^I \quad (\text{D.5})$$

and

$$\ln Pollution'_{i_R,R,t} = \ln Pollution_{i_R,t} + M'_{i_R,t} \rho^R. \quad (\text{D.6})$$

These two equations jointly imply that:

$$\ln Pollution'_{i_I, I, t} - \ln Pollution'_{i_R, R, t} = M'_{i_I, t} (\rho^I - \rho^R) = M'_{i_I, t} \rho, \quad (D.7)$$

provided that parcels i_I and i_R share the same initial pollution level (i.e., $\ln Pollution_{i_I, t} = \ln Pollution_{i_R, t}$). Substituting this result into Equation (D.1) demonstrates that:

$$\ln Pollution_{g(i_I), \tau}^{\text{obs}} - \ln Pollution_{g(i_R), \tau}^{\text{obs}} = M'_{i_I, t} \rho + \epsilon_{g(i_I), \tau} - \epsilon_{g(i_R), \tau}. \quad (D.8)$$

Given that the combined idiosyncratic term, $\epsilon_{g(i_I), \tau} - \epsilon_{g(i_R), \tau}$, is orthogonal to the attribute vector $M_{i_I, t}$, the coefficient vector ρ can be consistently estimated using the OLS estimator.

In our empirical context, however, the identification of a perfectly comparable residential parcel for each industrial parcel proves to be an overly stringent requirement. Indeed, the candidate pool for matching is already severely constrained, even when solely considering the criterion of proximate initial pollution levels. Therefore, as a fallback strategic, we match each industrial parcel with a residential parcel transacted within the same city and year-quarter that exhibits the closest initial pollution level, irrespective of other land attributes. Even with these relaxed matching criteria, 825 (approximately 4.9%) of industrial parcels still demonstrate an absolute difference in initial $PM_{2.5}$ concentration exceeding $5 \mu\text{g}/\text{m}^3$ when compared to their matched residential counterparts, and 5,713 (approximately 34.1%) of industrial parcels exhibit an absolute difference exceeding $1 \mu\text{g}/\text{m}^3$. While this matching procedure does not guarantee the comparability of all land attributes, any potential bias introduced by this approach is likely to be insubstantial, as long as the pollution increase attributable to residential parcels is relatively mild.

In Table 4, we present the results in Columns (2) to (4), corresponding to estimations utilizing all industrial parcels, and those restricted to industrial parcels matched with residential parcels where the absolute difference in $PM_{2.5}$ concentration during the transaction year-quarter is less than $5 \mu\text{g}/\text{m}^3$ and $1 \mu\text{g}/\text{m}^3$, respectively.

To test whether the four sets of point estimates presented in Table 4 imply systematically divergent pollution predictions, we utilize these four sets of coefficients to compute four corresponding sets of predictions for the difference in counterfactual pollution levels between industrial and residential land uses. This analysis is conducted across the 48,422 parcels transacted during 2012Q4 to 2013Q3 in Wave 1 cities. For visualization purposes, each set of predictions is normalized to have a zero mean, as their absolute mean values do not influence the estimation of preference parameters within the local governments' utility function. Figure D.1 illustrates two distinct comparative analyses. Specifically, Panel A compares predictions derived from the coefficients in Column (1) with those from Column (2), thereby assessing the robustness of our findings to the selection of control groups for industrial land parcels. Panel B, conversely, compares predictions based on the coefficients in Column (2) against those in Column (4), to investigate whether variations in the degree of comparability among residential parcels introduce a substantial divergence in the predictions. As depicted, both panels demonstrate broad consistency. However, the divergence between the two sets of predictions presented in Panel A is noticeably more pronounced. Reassuringly, the application of

these different sets of predictions to estimate local governments' post-monitoring utility functions in Table E.9 yields consistent conclusions.

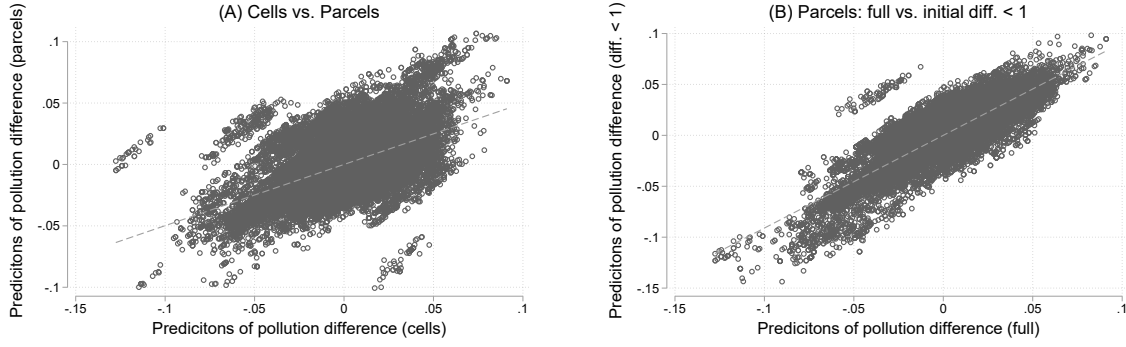


Figure D.1: Comparison of pollution difference predictions: cell-based vs. parcel-based

Notes: This figure presents a comparative analysis of predicted pollution differences between industrial and residential land uses, derived from various estimations. Specifically, four distinct sets of coefficients, sourced from Table 4, are utilized to compute counterfactual pollution differences for the 48,422 parcels transacted in Wave 1 cities between 2012Q4 and 2013Q3. Each dot in the figure represents a land parcel. All sets of predictions are centered to possess a zero mean. Panel A presents a comparison between predictions derived from the coefficients in Column (1) and those in Column (2) of Table 4. Panel B compares predictions obtained from the coefficients in Column (2) with those from Column (4).

D.2 Using four-quarter average pollution levels for matching and estimation

As discussed in the main text, a potential concern arises regarding the susceptibility of our matching procedure—which relies on pollution levels from a single quarter for matching and a single post-transaction quarter for estimating counterfactual pollution—to quarter-specific shocks. For instance, if a parcel is transacted in the fourth quarter, the $\tau = t + 12$ quarter used for estimation will also fall in the fourth quarter of a year. Consequently, the inherently higher absolute levels of pollution observed during winter months could lead to a substantial observed difference in pollutant concentration between industrial land parcels and non-transacted grid cells. While our logarithmic transformation effectively mitigates the influence of seasonal variations in absolute pollution levels, we deem it necessary to provide a formal robustness check for this concern.

The procedure begins by constructing a 2.5-kilometer buffer zone around each industrial land parcel transacted between 2012Q4 and 2016Q3, and then excluding grid cells situated within these buffer zones. The remaining grid cells constitute the set O_c for each city. For each industrial land parcel i in city c , transacted between 2012Q4 and 2013Q3, we identify cells $i' \in O_c$ that satisfy the following $PM_{2.5}$ concentration difference criterion: $-2 < Pollution_{g(i),t'} - Pollution_{g(i'),t'} < 2$ for all $t' \in \{t - 3, t - 2, t - 1, t\}$. This implies that the matched grid cells must exhibit comparable pollution levels across the transaction quarter and the three preceding quarters. These selected non-transacted cells form the control group $O_c(i)$ for parcel i . On average, 208 cells are matched to each industrial land parcel. Subsequently, we utilize the average $PM_{2.5}$ concentration during the third post-transaction year ($9 \leq \tau \leq 12$) to calculate the left-hand side of Equation (15), and then estimate this regression function. With the estimated coefficients, we predict the expected difference in

counterfactual pollution levels between industrial and residential land use for each parcel transacted during 2012Q4 to 2013Q3 in Wave 1 cities.

Figure D.2 presents a comparison between the two cell-based methods. Overall, a strong correlation is observed between them. Furthermore, we note that the variance of predictions derived from the four-quarter average $PM_{2.5}$ concentration is smaller, which is consistent with our expectation that averaging mitigates a substantial portion of inter-quarter variation. However, it is important to acknowledge that this procedure might concurrently eliminate valuable variation crucial for the identification of local governments' objective function. We also assess the sensitivity of our estimates of local governments' utility function by substituting the quarter-based predictions with those derived from this alternative procedure in Table E.9, and the findings suggest that our results are robust.

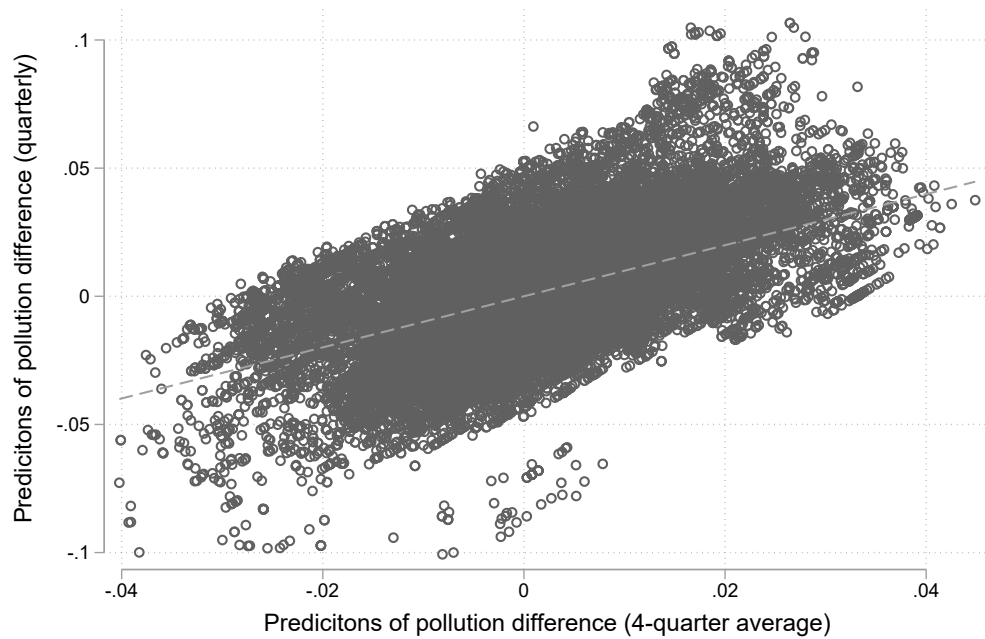


Figure D.2: Comparison of pollution difference predictions: quarterly vs. four-quarter average

Notes: This figure presents a comparative analysis of predicted pollution differences between industrial and residential land uses, derived from two distinct cell-based methods. The first method involves matching industrial parcels with non-transacted grid cells based on $PM_{2.5}$ concentration in the transaction quarter, with subsequent estimation relying on $PM_{2.5}$ concentration in the twelfth post-transaction quarter. The second method matches industrial parcels using the average $PM_{2.5}$ concentration across the transaction quarter and the three preceding quarters, and estimates are based on the average $PM_{2.5}$ concentration in the third post-transaction year. Each dot in the figure represents one of the 48,422 parcels transacted in Wave 1 cities between 2012Q4 and 2013Q3. Two sets of predictions are both centered to have a zero mean.

E Additional figures and tables

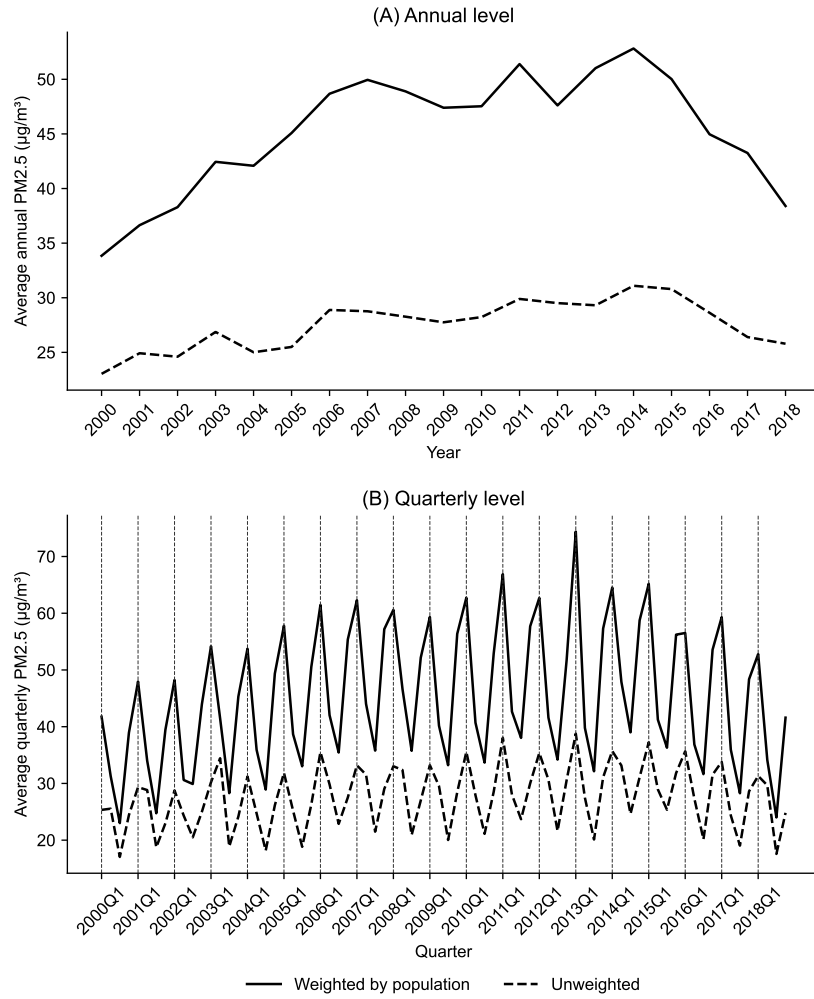


Figure E.1: Average $PM_{2.5}$ concentration during 2000 to 2018 in China

Notes: This figure illustrates the average $PM_{2.5}$ concentrations in China from 2000 to 2018. The underlying data are derived from satellite-based $PM_{2.5}$ estimates, encompassing both annual and monthly measurements, which were constructed by the Atmospheric Composition Analysis Group (Shen et al., 2024). Specifically, we employ their V6.GL.02.04 dataset, which offers $PM_{2.5}$ concentration estimates at a spatial resolution up to $0.01^\circ \times 0.01^\circ$ cells. The $0.01^\circ \times 0.01^\circ$ annual dataset is utilized for calculating annual averages, while the $0.1^\circ \times 0.1^\circ$ monthly dataset serves as the basis for quarterly averages. The unweighted line represents the simple average across all cells. To accurately reflect the pollution levels experienced by residents, each cell is weighted by its corresponding population count. For this purpose, we utilize the Gridded Population of the World (GPWv4) dataset, provided by NASA (Version 4.11). This dataset furnishes estimates of the number of persons per pixel, based on the 2010 national census, at a resolution of $0.0083^\circ \times 0.0083^\circ$ cells. This estimated 2010 population distribution is then consistently applied as the weight for $PM_{2.5}$ concentrations for each year/quarter. Given the differing resolutions between the two datasets, they are matched based on the closest centroids.

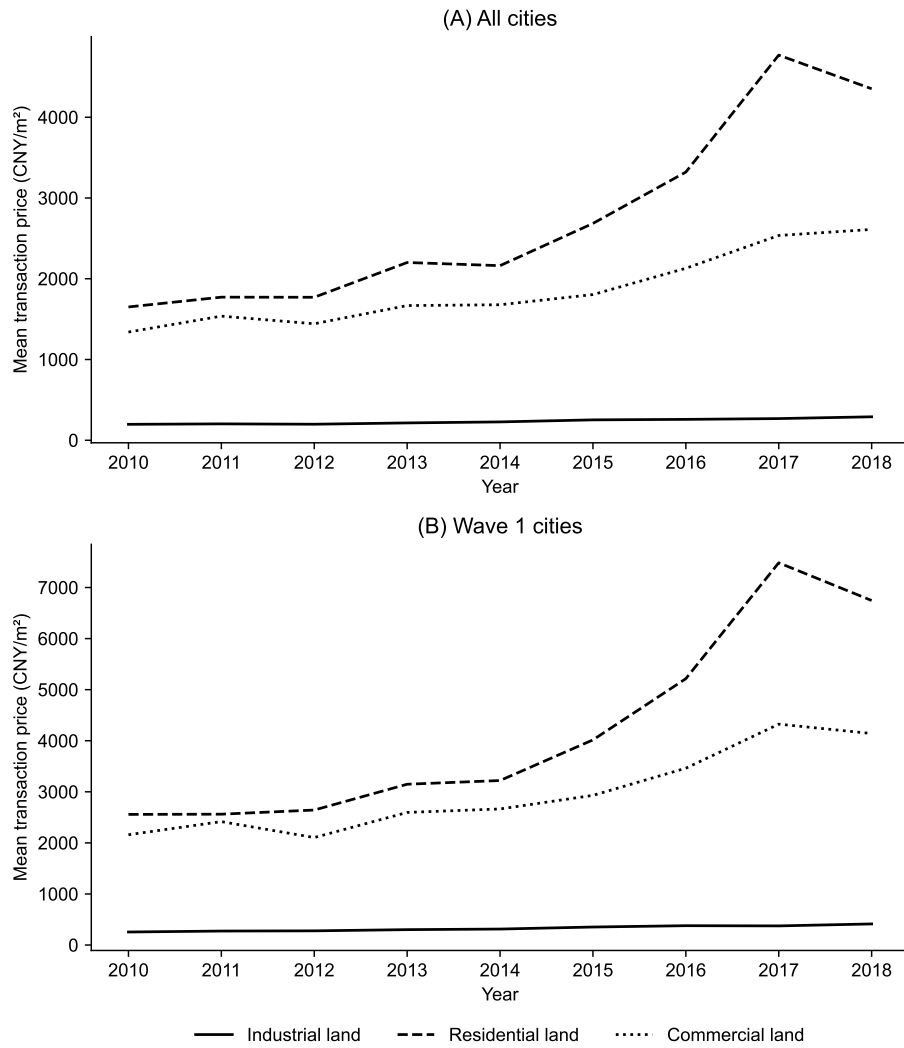


Figure E.2: Average land transaction price per unit by land types during 2010 to 2018 in China

Notes: This figure illustrates the average land transaction price per unit for three categories of urban construction land: industrial, residential, and commercial. To mitigate the influence of extreme values, unit prices are winsorized at the 99th percentile (the largest 1%) annually. For each year and land type, the unit price for each land parcel transaction is first calculated, and subsequently, the average weighted by land size is computed. Panel A presents the average unit price for all cities in our dataset. Panel B presents the average unit price specifically for the 74 cities that installed automatic atmospheric monitoring stations during the first wave of the national rollout (see Table E.1 for a detailed list). These cities are typically at a higher administrative level and exhibit greater economic development.

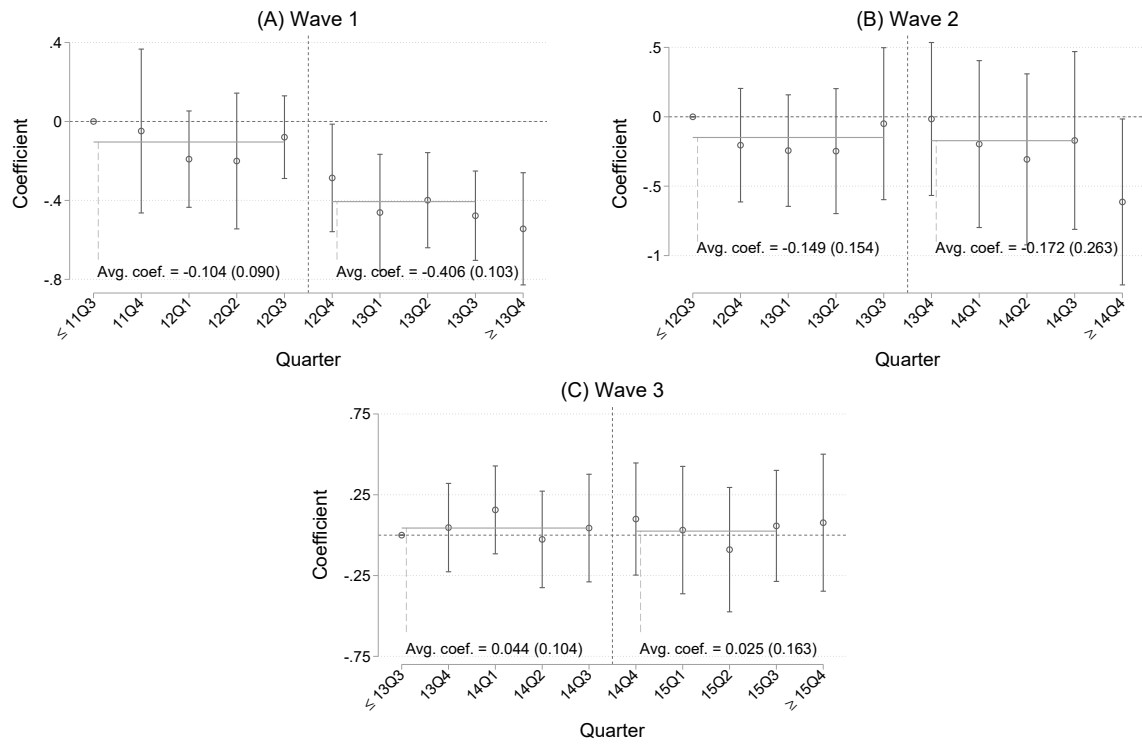


Figure E.3: Temporal changes in the pollution elasticity of residential land price using annual $PM_{2.5}$ level

Notes: This figure illustrates the estimated temporal evolution of the elasticity of residential land price with respect to pollution, derived from event study analyses for cities in three waves of the national rollout. A key distinction between this figure and Figure 2 is that Equation (10) is estimated using annual $PM_{2.5}$ levels instead of quarterly levels. Point estimates are represented by circles, with lines indicating 95% confidence intervals. Average coefficients for pre-monitoring periods and for the four quarters following monitoring are estimated using the delta method, with corresponding standard errors presented in parentheses. This figure demonstrates patterns consistent with Figure 2, specifically indicating that only Wave 1 cities experienced a decline in the residential land price elasticity with respect to pollution immediately subsequent to monitoring.



Figure E.4: Average PM_{2.5} concentration in cities across three waves from 2000 to 2018

Notes: This figure illustrates the population-weighted average PM_{2.5} concentrations in cities across three waves spanning the period 2000 to 2018. The data sources and calculation methodology are identical to those detailed in the notes of Figure E.1.

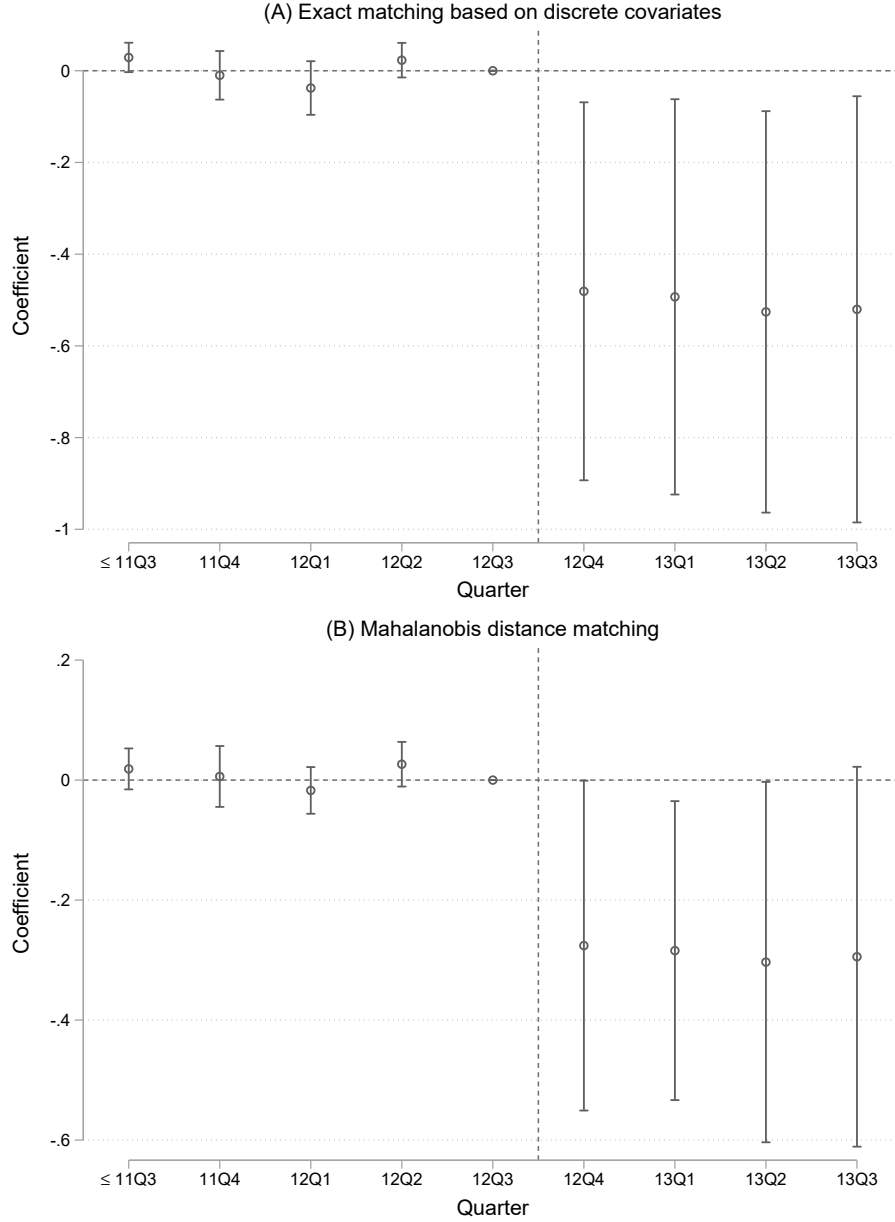


Figure E.5: Event study for the ATT on the pollution elasticity of residential land price in Wave 1 cities

Notes: This figure presents the estimates derived from the following event study specification, with point estimates represented by circles and 95% confidence intervals, based on standard errors clustered at the city level, indicated by lines:

$$\ln \text{UnitPrice}_{i,t} = c_0 + \sum_{m=-5}^4 \phi_m \cdot \ln \text{Pollution}_{i,t} \times \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times \mathbf{1}\{R_{c(i),t} = m\} + c_1 \cdot \mathbf{1}\{\text{Wave } 1\}_{c(i)} \times \text{After}_t \\ + \sum_c c_2^c \cdot \ln \text{Pollution}_{i,t} \times \delta_{c(i)}^R + \sum_t c_3^t \cdot \ln \text{Pollution}_{i,t} \times v_t + \delta_{c(i)} + v_t + \mathbf{X}_t' \boldsymbol{\beta} + \epsilon_{i,t}.$$

This specification is identical to those presented in Columns (3) and (5) of Table 1, with the sole exception that the After_t term in the triple-differences interaction is replaced by a set of year-quarter dummies. Matching samples, constructed using two distinct procedures, are employed in this figure. Both procedures were executed within year-quarter and land type strata. The first procedure, the results of which are presented in Panel A, commenced with an exact matching on four discrete covariates (e.g., rank, transaction mechanism). Subsequently, within the exactly matched sample, Mahalanobis distance matching was applied using continuous covariates (e.g., distance to the population center, pollution level). The second procedure, presented in Panel B, involved the transformation of discrete covariates into dummy variables, which were subsequently integrated with all continuous covariates for the purpose of Mahalanobis distance matching. Each parcel was matched with its four nearest neighbors, where applicable.

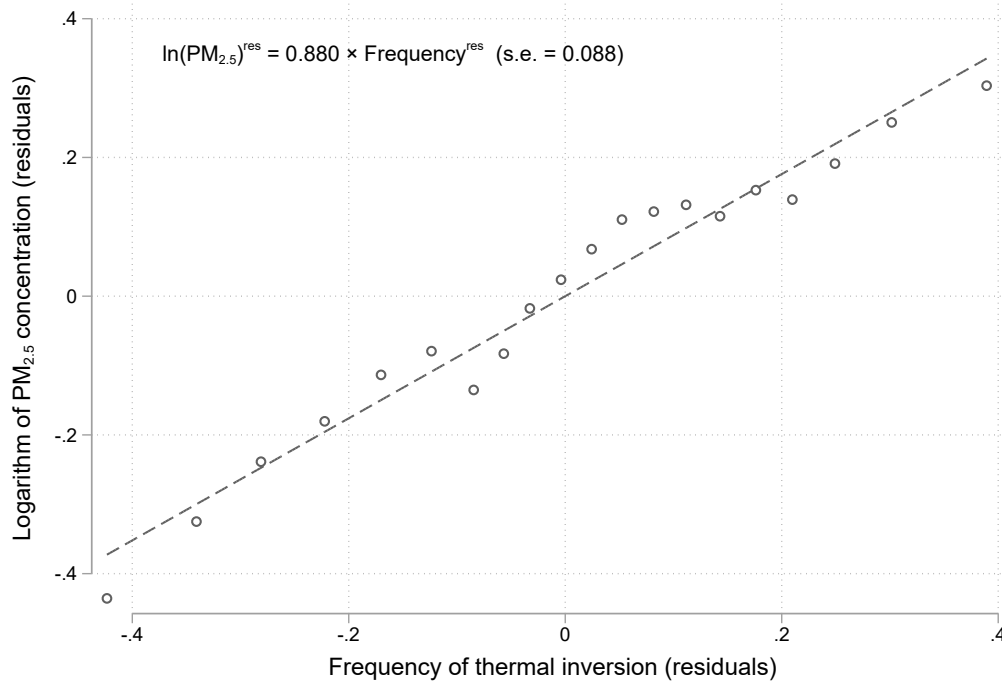


Figure E.6: Binscatter plot between PM_{2.5} concentration and the frequency of thermal inversion

Notes: This figure presents a binscatter plot illustrating the relationship between PM_{2.5} concentration and the frequency of the thermal inversion phenomenon. The estimation sample is derived from the land parcel dataset. Each observation corresponds to a land parcel, for which the PM_{2.5} concentration is sourced from a 0.01° × 0.01° cell (in the pollution dataset) and the thermal inversion frequency from a 0.625° × 0.5° cell (in the thermal inversion dataset), with both cells geographically aligned with the parcel. To account for the influence of land attributes (e.g., distance to the city population center, land rank), we first regress both the PM_{2.5} concentration and the thermal inversion frequency on these attributes, and subsequently utilize the derived residuals for this plot.

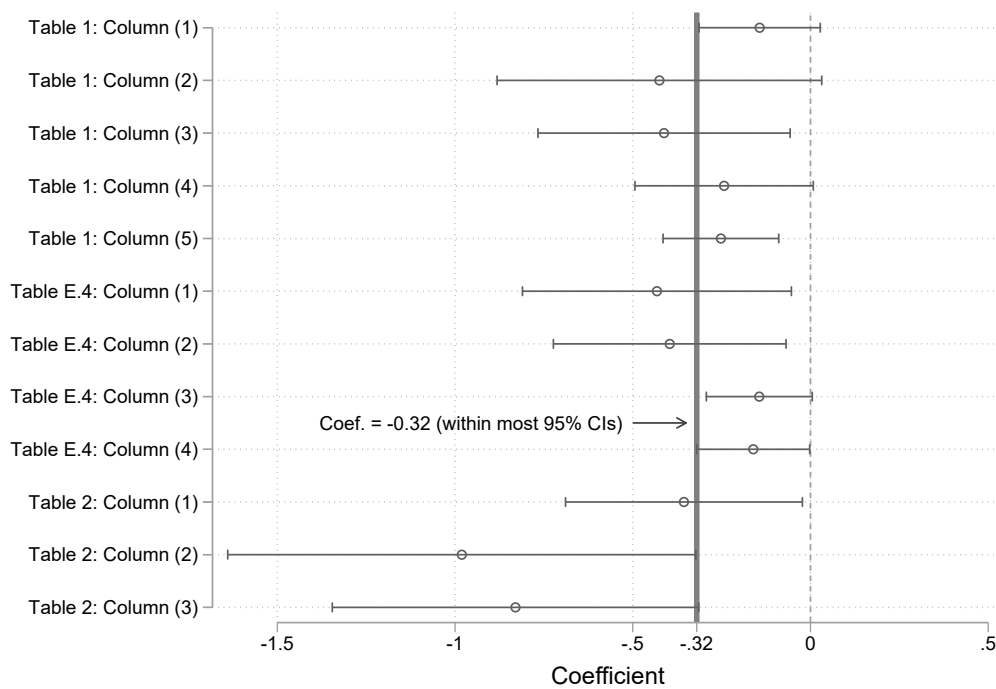


Figure E.7: Summary of estimated treatment effects on pollution elasticity of residential land price

Notes: This figure summarizes the estimates for ϕ in Equation (11). From top to bottom, the first five rows, sourced from Table 1, present estimates of the ATT on the pollution elasticity of residential land prices in Wave 1 cities, derived by comparing parcels in Wave 1 cities with those in Wave 2 and Wave 3 cities. The sixth through ninth rows, from Table E.4, employ only Wave 3 cities as the control group. The tenth through twelfth rows are taken from Table 2, where the 2SLS estimator is utilized. Estimates from Appendix Table E.6 are excluded from this summary, as the associated first-stage F-statistic was deemed too small to yield reliable point estimates. Dots represent the point estimates, and lines denote the 95% confidence intervals. The value of -0.32 is highlighted, as this value is covered by most of the confidence intervals.

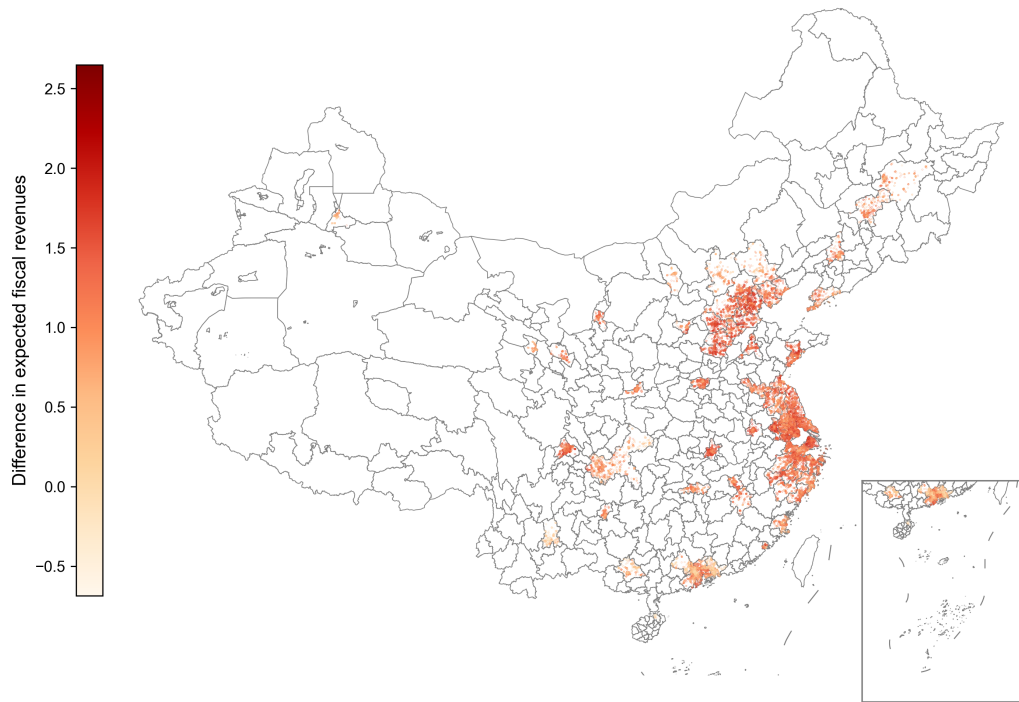


Figure E.8: Differences in expected fiscal revenues for land parcels after monitoring

Notes: This figure illustrates the estimated expected fiscal revenue differential for a given parcel, representing the difference in revenue per unit if it were designated for industrial use compared to residential use, which is captured by $\ln V_{n,i,I,t}^1 - \ln V_{n,i,R,t}^1$ in the theoretical framework, for 48,422 land parcels transacted between 2012Q4 and 2013Q3 in Wave 1 cities. Each dot signifies a single land parcel.

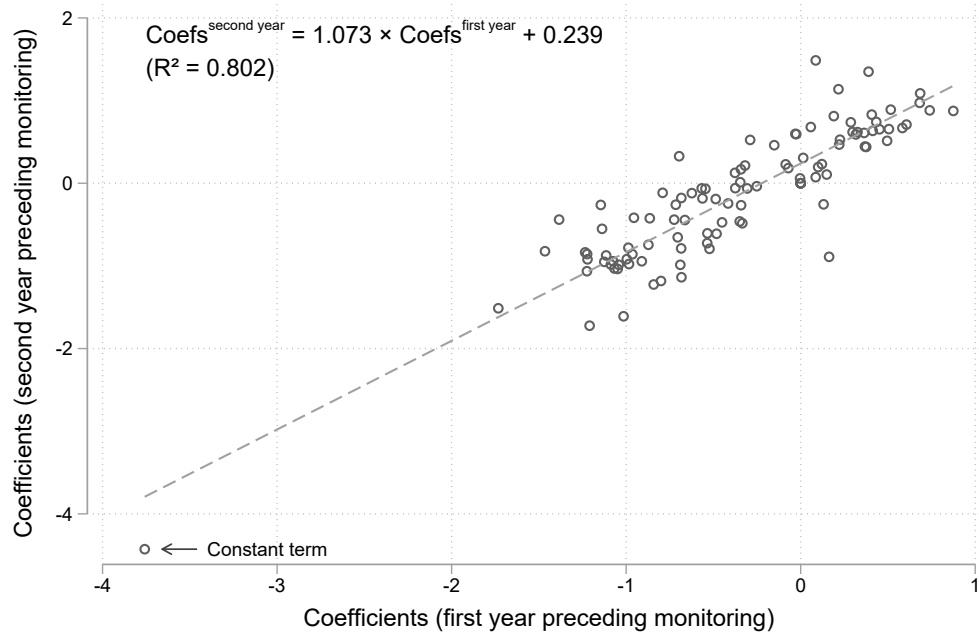


Figure E.9: Short-term stability of coefficients in the expected fiscal revenue function

Notes: This figure illustrates the coefficients estimated from Equation (3) using two distinct estimation samples: land transaction records from the year immediately preceding the establishment of monitoring stations in Wave 1 cities (2011Q4 to 2012Q3), and records from the second year prior to monitoring (2010Q4 to 2011Q3). Given the potential for heterogeneity in preference parameters between these two periods, all coefficients obtained from the earlier sample are adjusted by a uniform scaling factor to equalize their estimates for the coefficient of $\ln Pollution_{i,t}$. Each dot represents the two coefficient estimates of either a continuous variable (e.g., pollution, distance to the city population center) or a dummy variable for discrete land attributes, city fixed effects, or quarter fixed effects. The dashed line represents the fitted line of the scatter plot.

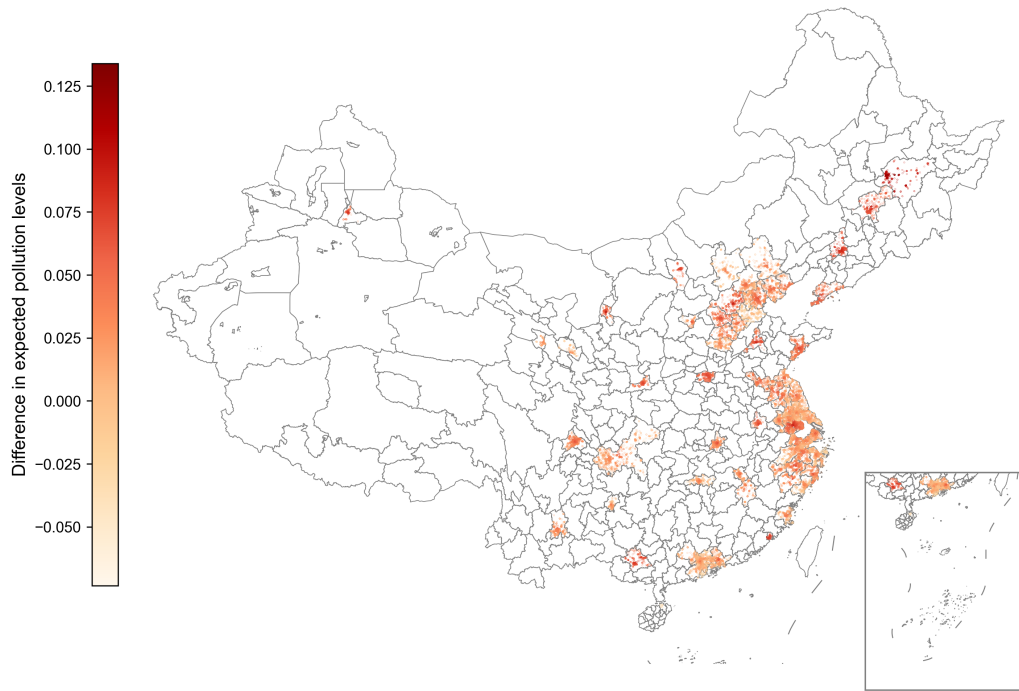


Figure E.10: Differences in expected counterfactual pollution levels for land parcels after monitoring

Notes: This figure illustrates the estimated expected difference in pollution levels for a given parcel. Specifically, it represents the counterfactual difference in pollution levels caused by unit area of the parcel, assuming it were designated for industrial use versus residential use. This differential is formally expressed as $\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}$ in the theoretical framework. The depicted data pertains to 48,422 land parcels transacted between 2012Q4 and 2013Q3 in Wave 1 cities, with each dot representing an individual land parcel.

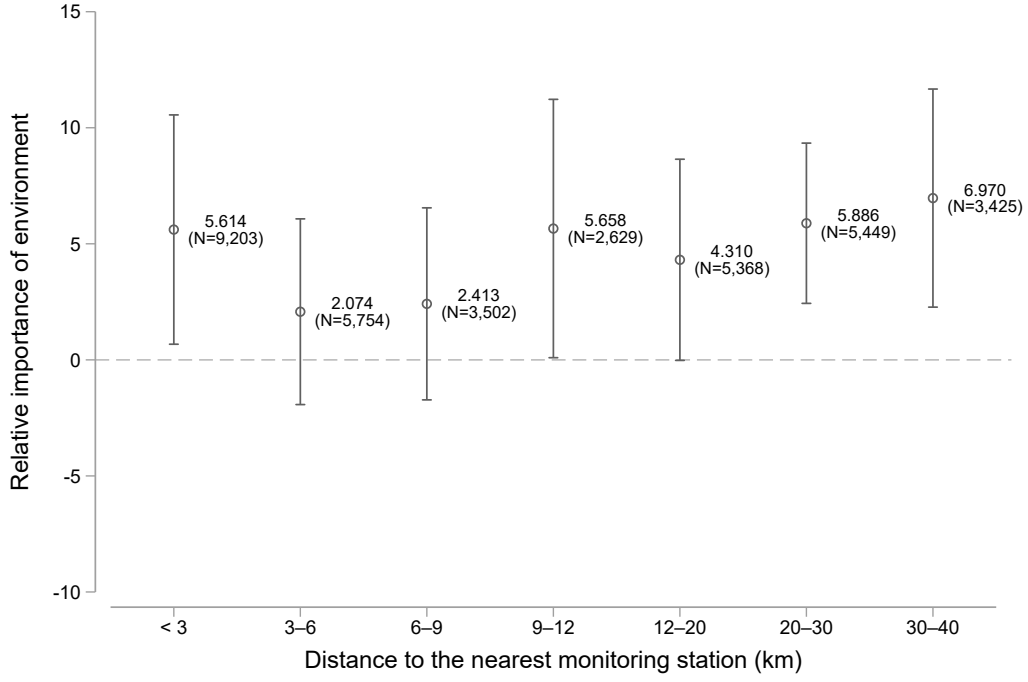


Figure E.11: Ring analysis using pre-monitoring transaction data

Notes: This figure presents a falsification test, replicating the ring analysis from Figure 4 using parcels transacted during the second pre-monitoring year (i.e., 2010Q4 to 2011Q3) in Wave 1 cities. In this figure, each dot represents the ratio of two point estimates, specifically $\hat{\theta}^1$ (for pollution) and $\hat{\alpha}^1$ (for fiscal revenue) corresponding to a specific distance bin. For instance, the dot in the first column depicts the ratio between the estimated coefficient on $(\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}) \times D_i^{0-3}$ and the estimated coefficient on $(\ln V^1_{n,i,I,t} - \ln V^1_{n,i,R,t}) \times D_i^{0-3}$. Each line indicates the corresponding 95% confidence interval, computed using the delta method. The exact point estimates and the number of land parcels in each subsample are presented directly in the figure.

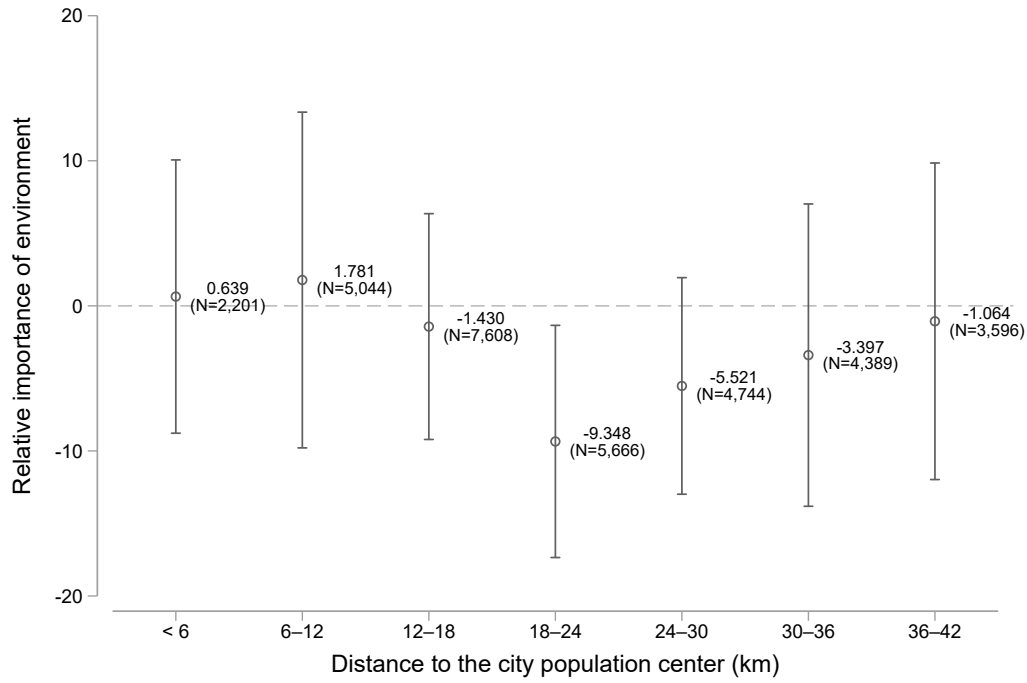


Figure E.12: Ring analysis based on the distance to the city population center

Notes: This figure presents a falsification test, replicating the ring analysis from Figure 4 but stratifying parcels based on their distance to the city population center, rather than to the nearest monitoring station. The distance bins were adjusted to avoid excessively sparse observations in the initial columns. Each dot in the figure represents the ratio of two point estimates: specifically, $\hat{\theta}^1$ (for pollution) and $\hat{\alpha}^1$ (for fiscal revenue), corresponding to a specific distance bin. Each line indicates the corresponding 95% confidence interval, which is computed using the delta method. The precise point estimates and the number of land parcels in each subsample are directly presented within the figure.

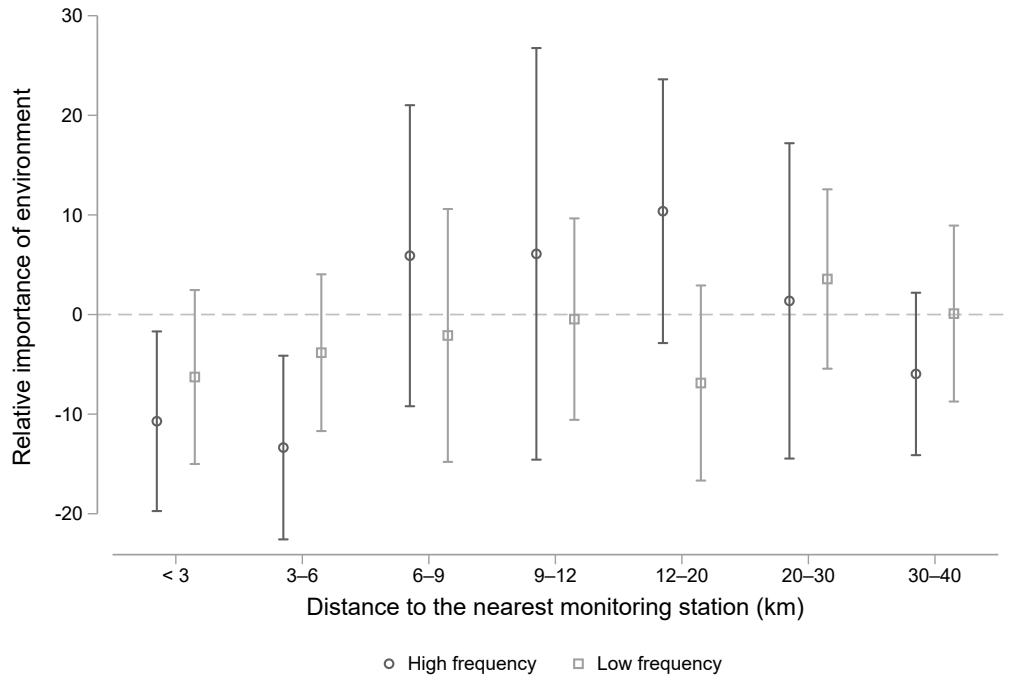


Figure E.13: Ring analysis: heterogeneity by historical environmental protection emphasis

Notes: This figure illustrates the results of a ring analysis conducted on two distinct subsamples of land parcels transacted during 2012Q4 to 2013Q3 in Wave 1 cities. The “high frequency” group encompasses parcels located in cities where the environment-related keyword frequency exceeded the median level in 2011. The “low frequency” group comprises the remaining parcels in Wave 1 cities. Each dot in the figure represents the ratio of two point estimates: specifically, $\hat{\theta}^1$ (for pollution) and $\hat{\alpha}^1$ (for fiscal revenue), corresponding to a specific distance bin. Each line indicates the corresponding 95% confidence interval, which is computed using the delta method.

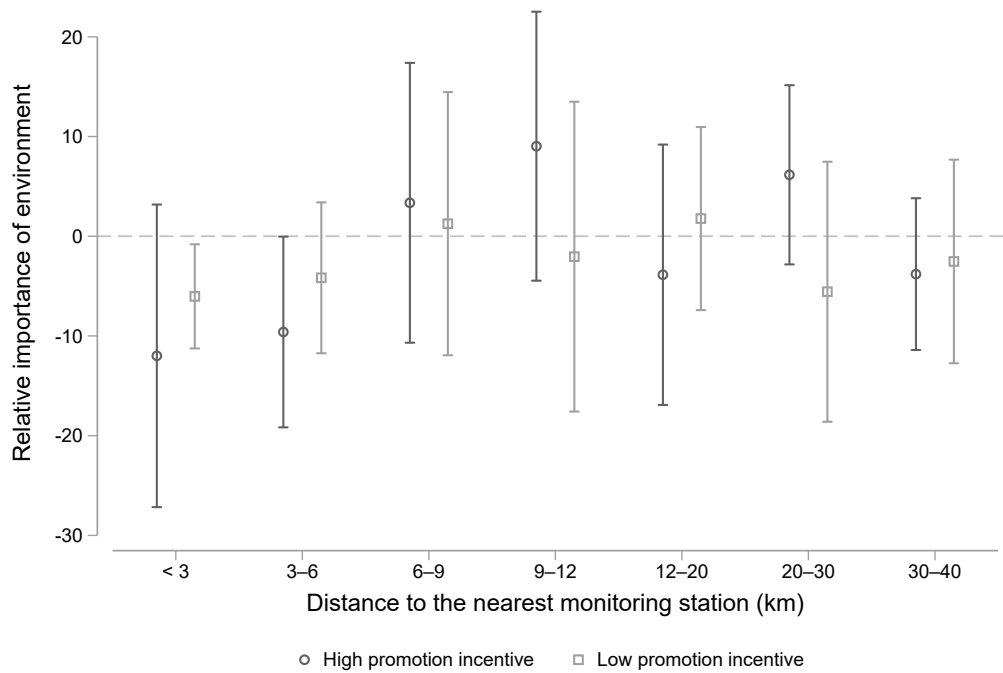


Figure E.14: Ring analysis: heterogeneity by promotion incentive

Notes: This figure illustrates the results of a ring analysis conducted on two distinct subsamples of land parcels transacted during 2012Q4 to 2013Q3 in Wave 1 cities. The “high promotion incentive” group encompasses parcels located in cities where the estimated promotion likelihood the median level. The “low promotion incentive” group comprises the remaining parcels in Wave 1 cities. Each dot in the figure represents the ratio of two point estimates: specifically, $\hat{\theta}^1$ (for pollution) and $\hat{\alpha}^1$ (for fiscal revenue), corresponding to a specific distance bin. Each line indicates the corresponding 95% confidence interval, which is computed using the delta method.

Table E.1: Cities in each wave of the rollout of the national atmospheric monitoring network

Wave	City
Wave 1 (December 2012)	Shanghai, Dongguan, Zhongshan, Lishui, Urumqi, Foshan, Baoding, Lanzhou, Beijing, Nanjing, Nanning, Nanchang, Nantong, Xiamen, Taizhou, Hefei, Hohhot, Harbin, Tangshan, Jiaxing, Dalian, Tianjin, Taiyuan, Ningbo, Suqian, Changzhou, Guangzhou, Langfang, Zhangjiakou, Xuzhou, Huizhou, Chengdu, Yangzhou, Chengde, Fuzhou, Lhasa, Wuxi, Kunming, Hangzhou, Wuhan, Jiangmen, Shenyang, Cangzhou, Taizhou, Jinan, Haikou, Huaian, Shenzhen, Wenzhou, Huzhou, Zhuhai, Yancheng, Shijiazhuang, Fuzhou, Qinhuangdao, Shaoxing, Zhaoqing, Zhoushan, Hengshui, Quzhou, Xining, Xi'an, Guiyang, Lianyungang, Xingtai, Handan, Zhengzhou, Chongqing, Jinhua, Yinchuan, Zhenjiang, Changchun, Changsha, Qingdao (<i>74 cities</i>)
Wave 2 (October 2013)	Sanya, Sanmenxia, Dongying, Linfen, Linyi, Dandong, Jiujiang, Yunfu, Karamay, Baotou, Beihai, Nanchong, Jilin, Xianyang, Jiayuguan, Datong, Daqing, Weihai, Anyang, Yibin, Yichang, Baoji, Yueyang, Bayingol, Changde, Pingdingshan, Yan'an, Kaifeng, Zhangjiajie, Dezhou, Deyang, Fushun, Jieyang, Panzhihua, Rizhao, Qijing, Benxi, Zaozhuang, Liuzhou, Zhuzhou, Guilin, Meizhou, Shantou, Shanwei, Heyuan, Quanzhou, Tai'an, Luzhou, Luoyang, Jining, Zibo, Qingyuan, Weinan, Xiangtan, Zhanjiang, Binzhou, Weifang, Chaozhou, Yantai, Jiaozuo, Mudanjiang, Yuxi, Panjin, Shizuishan, Mianyang, Liaocheng, Zigong, Wuhu, Suzhou, Maoming, Jingzhou, Heze, Yingkou, Huludao, Chifeng, Zunyi, Ordos, Jinchang, Tongchuan, Jinzhou, Changzhi, Yangjiang, Yangquan, Anshan, Shaoguan, Ma'anshan, Qiqihar (<i>87 cities</i>)
Wave 3 (November 2014)	Qitaihe, Sanming, Shangrao, Zhongwei, Linxia, Lincang, Lijiang, Ulanqab, Wuhai, Leshan, Bozhou, Yichun, Ili, Jiamusi, Baoshan, Xinyang, Kizilsu, Lu'an, Liupanshui, Hinggan, Neijiang, Liangshan, Shiyang, Nanping, Nanyang, Bortala, Shuangyashan, Ji'an, Turpan, Lvliang, Wuzhong, Zhokou, Hulunbuir, Hotan, Xianning, Hami, Shangqiu, Shangluo, Kashgar, Siping, Guyuan, Tacheng, Daxing'anling, Dali, Tianshui, Loudi, Xiaogan, Ningde, Anqing, Ankang, Anshun, Dingxi, Yichun, Xuancheng, Suzhou, Shannan, Chongzuo, Bazhong, Bayannur, Pingliang, Guangyuan, Guang'an, Qinyang, Yanbian, Zhangye, Dehong, Xinzhong, Huaihua, Nujiang, Enshi, Wenshan, Xinxiang, Xinyu, Shigatse, Changji, Chamdo, Zhaotong, Jinzhong, Jincheng, Pu'er, Jingdezhen, Shuozhou, Chaoyang, Laibin, Songyuan, Nyingchi, Golog, Wuzhou, Chuxiong, Yulin, Wuwei, Bijie, Yongzhou, Hanzhong, Chizhou, Hechi, Haidong, Haibei, Hainan, Haixi, Huaipei, Huainan, Xiangxi, Chuzhou, Luohe, Zhangzhou, Puyang, Yulin, Yushu, Gannan, Garzê, Baicheng, Baishan, Baiyin, Baise, Yiyang, Meishan, Honghe, Suihua, Jingmen, Putian, Pingxiang, Bengbu, Hengyang, Xiangyang, Xishuangbanna, Xuchang, Guigang, Hezhou, Ziyang, Ganzhou, Liaoyuan, Liaoyang, Dazhou, Yuncheng, Diqing, Tonghua, Tongliao, Suining, Nagqu, Shaoyang, Chenzhou, Ezhou, Jiuquan, Qinzhou, Tieling, Tongren, Tongling, Xilingol, Fuxin, Fuyang, Fangchenggang, Aksu, Altay, Ngawa, Alxa, Ngari, Longnan, Suizhou, Ya'an, Zhumadian, Jixi, Hebi, Hegang, Yingtan, Huanggang, Huangnan, Huangshan, Huangshi, Heihe, Qiandongnan, Qiannan, Qianxinan, Longyan (<i>174 cities</i>)

Notes: This table enumerates the cities included in each wave of the rollout of the national atmospheric monitoring network. This list differs slightly from those presented in other studies, as we aggregate all county-level cities to their corresponding prefecture-level administrative regions to ensure comparability of administrative levels. The sole exceptions are Beijing, Tianjin, Shanghai, and Chongqing, four direct-administered municipalities (provincial-level cities), which are treated as unitary entities, consistent with other prefecture-level administrative regions. After 2015, the monitoring network encompasses these four municipalities and 331 out of 333 prefecture-level administrative regions. The only two cities not included are Sansha and Danzhou in Hainan Province. The official city lists for the three waves are accessible via: <https://www.mee.gov.cn/gkml/hbb/bgt/201205/W020120524383009550407.pdf> for Wave 1, <https://www.mee.gov.cn/gkml/hbb/bgt/201303/W020130328510299736496.pdf> for Wave 2, and <https://www.mee.gov.cn/gkml/hbb/bwj/201405/W020140509376439653789.pdf> for Wave 3 (all accessed December 2025).

Table E.2: Changes in pollution elasticity of land price after monitoring

	Dependent variable: Logarithm of unit price of land parcel					
	Residential land			Industrial land		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A. Wave 1 cities</i>						
$\ln(\text{PM}_{2.5}) \times \text{After}$	-0.206** (0.078)	-0.262** (0.118)	-0.246*** (0.088)	-0.077* (0.039)	-0.085 (0.076)	-0.087 (0.056)
$\ln(\text{PM}_{2.5})$	0.169 (0.108)	0.776*** (0.200)	0.608*** (0.138)	0.179** (0.073)	0.458*** (0.107)	0.202** (0.084)
$\ln(\text{Dist. to pop. center})$	-0.291*** (0.039)	-0.270*** (0.036)	-0.130*** (0.029)	-0.165*** (0.018)	-0.158*** (0.018)	-0.061*** (0.014)
Linear trend	0.020*** (0.005)	0.015** (0.007)	0.013** (0.006)	0.004 (0.004)	-0.003 (0.007)	0.000 (0.006)
# of clusters	73	73	73	73	73	73
# of observations	230,802	230,802	230,795	125,237	125,218	125,204
<i>Panel B. Wave 2 cities</i>						
$\ln(\text{PM}_{2.5}) \times \text{After}$	-0.179 (0.119)	0.000 (0.150)	-0.003 (0.110)	0.008 (0.036)	0.053 (0.046)	0.029 (0.035)
$\ln(\text{PM}_{2.5})$	0.392** (0.167)	0.143 (0.158)	0.179 (0.111)	0.183*** (0.056)	0.263*** (0.081)	0.130** (0.058)
$\ln(\text{Dist. to pop. center})$	-0.215*** (0.046)	-0.206*** (0.046)	-0.097*** (0.022)	-0.096*** (0.018)	-0.096*** (0.018)	-0.042*** (0.013)
Linear trend	0.001 (0.011)	0.020** (0.010)	0.013** (0.006)	-0.002 (0.002)	0.001 (0.003)	0.002 (0.002)
# of clusters	87	87	87	87	87	87
# of observations	201,606	201,595	201,594	75,175	75,165	75,159
<i>Panel C. Wave 3 cities</i>						
$\ln(\text{PM}_{2.5}) \times \text{After}$	-0.045 (0.087)	-0.003 (0.122)	-0.034 (0.096)	-0.029 (0.039)	-0.066 (0.053)	-0.023 (0.051)
$\ln(\text{PM}_{2.5})$	0.362*** (0.103)	0.476*** (0.112)	0.259** (0.102)	0.192*** (0.054)	0.297*** (0.074)	0.146* (0.076)
$\ln(\text{Dist. to pop. center})$	-0.161*** (0.042)	-0.157*** (0.040)	-0.076*** (0.019)	-0.111*** (0.017)	-0.106*** (0.017)	-0.024*** (0.009)
Linear trend	0.001 (0.006)	0.005 (0.006)	0.007 (0.006)	-0.002 (0.003)	-0.002 (0.004)	-0.003 (0.005)
# of clusters	168	168	168	168	168	168
# of observations	315,018	315,018	315,009	90,923	90,923	90,900
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	No	No	Yes	No	No
City fixed effects	Yes	Yes	No	Yes	Yes	No
Province-year-quarter fixed effects	No	Yes	Yes	No	Yes	Yes
County fixed effects	No	No	Yes	No	No	Yes

Notes: This table presents the estimated change in the elasticity of land price with respect to pollution following the establishment of the national atmospheric monitoring network, based on the estimation of the following specification:

$$\ln \text{UnitPrice}_{i,t} = \alpha_0 + \alpha_1 \cdot \ln \text{Pollution}_{i,t} + \varphi \cdot \ln \text{Pollution}_{i,t} \times \text{After}_{c(i),t} + \alpha_2 \cdot \ln \text{Pollution}_{i,t} \times t + \mathbf{X}_i' \boldsymbol{\beta} + \delta_{c(i)} + \nu_t + \epsilon_{i,t},$$

where $\text{UnitPrice}_{i,t}$ is the unit price for land parcel i transacted in year-quarter t , $\text{Pollution}_{i,t}$ represents the $\text{PM}_{2.5}$ level at the location of parcel i in t , $\text{After}_{c(i),t}$ is a dummy equal to 1 for observations recorded after monitoring, and 0 otherwise, $\mathbf{X}_i$ is a vector of land parcel attributes, including its distance to the city population center, rank, source, transaction mechanism, and designated industry, $\delta_{c(i)}$ and ν_t represent city and year-quarter fixed effects, respectively, and $\epsilon_{i,t}$ is the error term. An interaction term between pollution and a continuous year-quarter trend is included to control for potential linear trends in land prices. Columns (2), (3), (5), and (6) incorporate additional, more granular fixed effects. Standard errors, clustered at the city level, are reported in parentheses. Across all estimates presented in the panels and columns, we only observe robust and statistically significant decreases in the elasticity of residential land price for Wave 1 cities, consistent with the evidence from event studies in Figure 2.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.3: ATT of national monitoring on the pollution elasticity of industrial land price in Wave 1 cities

	Dependent variable: Logarithm of unit price of land parcel				
	Full sample	Two-step matching		Mahalanobis matching	
	(1)	(2)	(3)	(4)	(5)
$\ln(\text{PM}_{2.5}) \times \text{Wave 1} \times \text{After}$	0.021 (0.054)	0.090 (0.085)	0.065 (0.077)	-0.026 (0.054)	-0.053 (0.032)
$\text{Wave 1} \times \text{After}$	-0.080 (0.212)	-0.348 (0.347)	-0.276 (0.318)	0.088 (0.215)	0.211* (0.127)
$\ln(\text{PM}_{2.5}) \times \text{Wave 1}$	-0.300*** (0.087)	-0.218** (0.092)		-0.178** (0.089)	
$\ln(\text{PM}_{2.5}) \times \text{After}$	-0.051* (0.028)	-0.091 (0.067)		-0.006 (0.029)	
$\ln(\text{PM}_{2.5})$	0.140*** (0.051)	0.046 (0.049)		0.012 (0.049)	
Wave 1	1.533*** (0.351)	1.072*** (0.372)		1.012*** (0.364)	
After	0.275** (0.112)	0.434 (0.278)		0.112 (0.120)	
Controls	Yes	Yes	Yes	Yes	Yes
$\ln(\text{PM}_{2.5}) \times \text{year-quarter FEs}$	No	No	Yes	No	Yes
$\ln(\text{PM}_{2.5}) \times \text{city FEs}$	No	No	Yes	No	Yes
Year-quarter fixed effects	No	No	Yes	No	Yes
City fixed effects	No	No	Yes	No	Yes
# of clusters	327	286	286	286	286
# of parcels in Wave 1 cities	59,845	44,191	44,191	59,845	59,845
# of observations	141,540	71,795	71,795	109,987	109,987

Notes: This table presents estimates of the average treatment effect of national monitoring on the pollution elasticity of industrial land price in Wave 1 cities, derived from estimating Equation (11). Column (1) reports estimates obtained using the full sample, while Columns (2) to (5) utilize samples constructed via two distinct matching procedures. Both procedures were conducted within year-quarter and land type strata. The first procedure commenced with an initial exact matching on four discrete covariates (e.g., rank, transaction mechanism). Subsequently, within the exactly matched sample, Mahalanobis distance matching was then applied utilizing continuous covariates (e.g., distance to the population center, pollution level). The second procedure involved transforming discrete covariates into dummy variables, which were subsequently integrated with all continuous covariates for the purpose of Mahalanobis distance matching. In both cases, each parcel was matched with its four nearest neighbors, where applicable. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.4: ATT of national monitoring on pollution elasticity of residential land, with Wave 3 as control

	Dependent variable: Logarithm of unit price of land parcel			
	Two-step matching		Mahalanobis matching	
	(1)	(2)	(3)	(4)
<i>Panel A. Wave 1 vs. Wave 3</i>				
$\ln(\text{PM}_{2.5}) \times \text{Wave 1} \times \text{After}$	-0.432** (0.193)	-0.396** (0.167)	-0.144* (0.076)	-0.161** (0.081)
# of clusters	200	200	200	200
# of parcels in Wave 1 cities	88,416	111,324	104,605	132,044
# of observations	128,542	162,610	158,682	200,950
<i>Panel B. Wave 2 vs. Wave 3</i>				
$\ln(\text{PM}_{2.5}) \times \text{Wave 2} \times \text{After}$		-0.241** (0.101)		-0.176 (0.107)
# of clusters		213		213
# of parcels in Wave 2 cities		111,280		128,006
# of observations		173,182		204,814
Sample period	2010Q1– 2013Q3	2010Q1– 2014Q3	2010Q1– 2013Q3	2010Q1– 2014Q3
Controls	Yes	Yes	Yes	Yes
$\ln(\text{PM}_{2.5}) \times \text{year-quarter FEs}$	Yes	Yes	Yes	Yes
$\ln(\text{PM}_{2.5}) \times \text{city FEs}$	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes
City fixed effects	Yes	Yes	Yes	Yes

Notes: This table presents causal estimates of the average treatment effect of national monitoring on the pollution elasticity of residential land price for Wave 1 and Wave 2 cities, respectively. Panel A presents estimates of the average treatment effect for Wave 1 cities, while Panel B provides estimates for Wave 2 cities. These estimates are derived from Equation (11). For Panel B, After_t equals 1 in 2013Q4 and subsequent periods. A key distinction between this table and Table 1 is the exclusive use of land parcels in Wave 3 cities as the control group. Columns (1) and (3) utilize samples covering periods before 2013Q4, consistent with Table 1. In contrast, Columns (2) and (4) employ samples from all periods prior to 2014Q4, which represents the deadline quarter for cities in the third wave of the national rollout. Both sets of estimates utilize re-constructed matching samples. The two matching procedures detailed in the main text were applied. The first procedure involved initial exact matching based on four discrete covariates (e.g., rank, transaction mechanism). Subsequently, Mahalanobis distance matching was applied within the exactly matched sample, utilizing continuous covariates such as distance to the population center and pollution level. The second procedure transformed discrete covariates into dummy variables, which were then integrated with all continuous covariates for the purpose of Mahalanobis distance matching. In both procedures, each parcel was matched with its four nearest neighbors, where applicable. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.5: Estimating ATT on the pollution elasticity of industrial land price with instrumental variables

	Dependent variable: Logarithm of unit price of land parcel		
	Full sample	Two-step matching	Mahalanobis matching
	(1)	(2)	(3)
$\ln(\text{PM}_{2.5}) \times \text{Wave 1} \times \text{After}$	0.226 (0.185)	0.248 (0.229)	0.139 (0.175)
$\ln(\text{PM}_{2.5})$	0.037 (0.168)	-0.105 (0.123)	-0.124 (0.164)
Controls	Yes	Yes	Yes
Kleibergen–Paap F-statistic	17.210	8.258	18.877
# of clusters	327	286	286
# of parcels in Wave 1 cities	59,847	44,197	59,847
# of observations	141,542	71,801	109,989

Notes: This table reports estimates of the average treatment effect of national monitoring on the pollution elasticity of industrial land price in Wave 1 cities. Estimates are derived from Equation (11) using the Two-Stage Least Squares estimator. The frequency of thermal inversion serves as the instrumental variable for pollution, and is subsequently utilized to construct instruments for the endogenous interaction terms. For clarity, only the estimated coefficients of two key variables are presented in this table, though all other relevant variables are incorporated into the estimation. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.6: Estimating ATT on pollution elasticity of residential land price using instruments, with Wave 3 as control

	Dependent variable: Logarithm of unit price of land parcel			
	Two-step matching		Mahalanobis matching	
	(1)	(2)	(3)	(4)
<i>Panel A. Wave 1 vs. Wave 3</i>				
$\ln(\text{PM}_{2.5}) \times \text{Wave 1} \times \text{After}$	-2.167*** (0.491)	-2.186*** (0.455)	-1.343*** (0.510)	-1.645*** (0.512)
$\ln(\text{PM}_{2.5})$	-2.617*** (0.588)	-2.600*** (0.587)	-2.484*** (0.719)	-2.461*** (0.723)
Kleibergen–Paap F-statistic	3.988	3.885	4.052	3.953
# of clusters	200	200	200	200
# of parcels in Wave 1 cities	93,323	118,016	104,606	132,045
# of observations	123,129	155,649	141,620	178,995
<i>Panel B. Wave 2 vs. Wave 3</i>				
$\ln(\text{PM}_{2.5}) \times \text{Wave 2} \times \text{After}$		0.479 (0.458)		-0.025 (0.365)
$\ln(\text{PM}_{2.5})$		-0.731*** (0.270)		-0.915*** (0.289)
Kleibergen–Paap F-statistic		12.270		18.007
# of clusters		213		213
# of parcels in Wave 2 cities		111,288		128,011
# of observations		173,191		204,819
Sample period	2010Q1– 2013Q3	2010Q1– 2014Q3	2010Q1– 2013Q3	2010Q1– 2014Q3
Controls	Yes	Yes	Yes	Yes

Notes: This table presents causal estimates of the average treatment effect of national monitoring on the pollution elasticity of residential land price for Wave 1 and Wave 2 cities, respectively. Panel A presents estimates of the average treatment effect for Wave 1 cities, while Panel B provides estimates for Wave 2 cities. Estimates are derived from Equation (11) using the Two-Stage Least Squares estimator. The frequency of thermal inversion serves as the instrumental variable for pollution, and is subsequently utilized to construct instruments for the endogenous interaction terms. Only land parcels in Wave 3 cities serve as the control group. Columns (1) and (3) utilize samples covering periods before 2013Q4, consistent with Table 2. In contrast, Columns (2) and (4) employ samples from all periods prior to 2014Q4, which represents the deadline quarter for cities in the third wave of the national rollout. Both sets of estimates utilize re-constructed matching samples. The two matching procedures detailed in the main text were applied. For clarity, only the estimated coefficients of two key variables are presented in this table, though all other relevant variables are incorporated into the estimation. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.7: Estimating post-monitoring utility function of local governments with different estimators

	Dependent variable: $\mathbf{1}\{\text{Industrial land}\}$		
	(1)	(2)	(3)
<i>Panel A. Logit model</i>			
Difference in fiscal revenue	2.068*** (0.181)	2.064*** (0.181)	2.677*** (0.185)
Difference in pollution level	-13.319*** (2.936)		-8.214** (3.437)
Difference in pollution level (≥ 0)		-14.636*** (3.295)	
Estimated θ^1/α^1	-6.441	-7.092	-3.069
Standard error for estimated θ^1/α^1	1.413	1.586	1.277
<i>Panel B. Linear probability model</i>			
Difference in fiscal revenue	0.381*** (0.024)	0.381*** (0.024)	0.478*** (0.026)
Difference in pollution level	-2.227*** (0.506)		-1.544*** (0.549)
Difference in pollution level (≥ 0)		-2.394*** (0.563)	
Estimated θ^1/α^1	-5.838	-6.290	-3.231
Standard error for estimated θ^1/α^1	1.355	1.510	1.161
<i>Panel C. PPML estimator</i>			
Difference in fiscal revenue	1.110*** (0.108)	1.107*** (0.108)	1.454*** (0.119)
Difference in pollution level	-7.765*** (1.671)		-4.515** (1.850)
Difference in pollution level (≥ 0)		-8.661*** (1.913)	
Estimated θ^1/α^1	-6.998	-7.826	-3.105
Standard error for estimated θ^1/α^1	1.470	1.699	1.271
City fixed effects	Yes	Yes	Yes
Year-quarter fixed effects	No	No	Yes
# of clusters	73	73	73
# of observations	48,422	48,422	48,422

Notes: This table presents the estimation results of Equation (9) using three alternative estimation methods—the logit model, linear probability model, and PPML estimator. The explanatory variables are the differences in expected fiscal revenue, $\ln V_{n,i,I,t}^1 - \ln V_{n,i,R,t}^1$, and counterfactual pollution levels, $\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}$, between industrial and residential land use, as estimated in Section 6. The estimation sample comprises all land parcels transacted in Wave 1 cities during the period of 2012Q4 to 2013Q3. In Column (2), negative values of the estimated pollution differential for parcels are truncated to zero. Standard errors, clustered at the city level, are reported in parentheses. The ratio of the two point estimates, representing θ^1/α^1 , is also reported, with its standard error calculated using the delta method.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.8: Estimating the utility function with pre-monitoring transaction records

	Dependent variable: $\mathbf{1}\{\text{Industrial land}\}$		
	(1)	(2)	(3)
<i>Panel A. The first pre-monitoring year (2011Q4–2012Q3)</i>			
Difference in fiscal revenues	1.543*** (0.099)	1.541*** (0.098)	1.738*** (0.103)
Difference in pollution levels	1.766 (1.697)		–0.340 (1.765)
Difference in pollution levels (≥ 0)		1.864 (1.962)	
# of clusters	73	73	73
# of observations	37,905	37,905	37,905
<i>Panel B. The second pre-monitoring year (2010Q4–2011Q3)</i>			
Difference in fiscal revenues	1.611*** (0.104)	1.609*** (0.104)	1.738*** (0.103)
Difference in pollution levels	3.379* (1.748)		–0.340 (1.765)
Difference in pollution levels (≥ 0)		2.742 (1.859)	
# of clusters	73	73	73
# of observations	45,730	45,730	37,905
City fixed effects	Yes	Yes	Yes
Year–quarter fixed effects	No	No	Yes

Notes: This table reports the estimation results of Equation (9) using a probit model. Panels A and B utilize samples consisting of all land parcels transacted in Wave 1 cities during the first (2011Q4–2012Q3) and second (2010Q4–2011Q3) pre-monitoring years, respectively. Consequently, these regressions serve as a falsification test to examine whether environmental protection had already become a priority for local governments prior to the implementation of monitoring. The first explanatory variable is the difference in expected fiscal revenue, $\ln V_{n,i,I,t}^1 - \ln V_{n,i,R,t}^1$, calculated using the estimated coefficients from Column (1) of Table 3. The second explanatory variable is the difference in counterfactual pollution levels between industrial and residential land use, $\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t}$, re-estimated following the procedure outlined in Section 6.2 using land data from the corresponding periods. In Column (2), negative values of the estimated pollution differential are truncated to zero. Standard errors, clustered at the city level, are reported in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.9: Estimating the utility function with different methods for pollution differential predictions

	Dependent variable: $\mathbf{1}\{\text{Industrial land}\}$		
	(1)	(2)	(3)
<i>Panel A. Industrial parcels vs. Residential parcels</i>			
Difference in fiscal revenues	1.251*** (0.104)	1.253*** (0.103)	1.591*** (0.104)
Difference in pollution levels	-7.092*** (1.912)		-2.527 (1.931)
Difference in pollution levels (≥ 0)		-7.385*** (2.415)	
Estimated θ^1/α^1	-5.671	-5.893	-1.588
Standard error for estimated θ^1/α^1	1.649	1.972	1.231
# of clusters	73	73	73
# of observations	48,422	48,422	48,422
<i>Panel B. Industrial parcels vs. Non-transacted cells (4-quarter average)</i>			
Difference in fiscal revenues	1.240*** (0.098)	1.243*** (0.098)	1.582*** (0.097)
Difference in pollution levels	-10.454** (4.669)		-9.116** (4.568)
Difference in pollution levels (≥ 0)		-9.511* (5.250)	
Estimated θ^1/α^1	-8.431	-7.653	-5.764
Standard error for estimated θ^1/α^1	3.622	4.118	2.821
# of clusters	73	73	73
# of observations	48,422	48,422	48,422
City fixed effects	Yes	Yes	Yes
Year-quarter fixed effects	No	No	Yes

Notes: This table presents robustness checks regarding two alternative methods for estimating the difference in counterfactual pollution levels between industrial and residential land use. In Panel A, the pollution variable is calculated using the coefficients from Column (2) of Table 4, where the linear pollution function is estimated by comparing industrial parcels with residential parcels. In Panel B, the pollution variable is derived from a comparison between industrial parcels and non-transacted grid cells; specifically, matching is performed using the average PM_{2.5} concentration across the transaction quarter and the three preceding quarters, and the regression utilizes the average PM_{2.5} concentration in the third post-transaction year. In Column (2), negative values of the estimated pollution differential are truncated to zero. Standard errors, clustered at the city level, are reported in parentheses. The ratio of the two point estimates, θ^1/α^1 , is also reported, with its standard error calculated using the delta method.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table E.10: The full regression results of the ring analysis

	Dependent variable: $\mathbf{1}\{\text{Industrial land}\}$	
	Linear probability model	Probit model
	(1)	(2)
Difference in fiscal revenues $\times$ 0–3 km	0.314*** (0.042)	1.350*** (0.141)
Difference in pollution levels $\times$ 0–3 km	–2.587** (1.044)	–11.220** (4.561)
Difference in fiscal revenues $\times$ 3–6 km	0.294*** (0.044)	1.083*** (0.116)
Difference in pollution levels $\times$ 3–6 km	–1.987** (0.907)	–6.564* (3.455)
Difference in fiscal revenues $\times$ 6–9 km	0.283*** (0.042)	0.929*** (0.134)
Difference in pollution levels $\times$ 6–9 km	0.344 (1.441)	0.396 (4.768)
Difference in fiscal revenues $\times$ 9–12 km	0.316*** (0.039)	1.011*** (0.161)
Difference in pollution levels $\times$ 9–12 km	1.156 (1.672)	3.457 (5.367)
Difference in fiscal revenues $\times$ 12–20 km	0.373*** (0.045)	1.168*** (0.154)
Difference in pollution levels $\times$ 12–20 km	–0.212 (1.683)	–1.197 (5.239)
Difference in fiscal revenues $\times$ 20–30 km	0.362*** (0.061)	1.118*** (0.216)
Difference in pollution levels $\times$ 20–30 km	1.078 (1.435)	3.633 (4.256)
Difference in fiscal revenues $\times$ 30–40 km	0.385*** (0.045)	1.299*** (0.168)
Difference in pollution levels $\times$ 30–40 km	–1.006 (1.169)	–2.356 (4.381)
City fixed effects	Yes	Yes
# of clusters	73	73
# of observations	37,003	36,873

Notes: This table reports the full estimation results of our ring analysis. Column (1) estimates the following linear probability model:

$$\mathbf{1}\{\text{Industrial land}\}_{i,t} = \alpha^1 \cdot \left(\ln V_{n,i,I,t}^1 - \ln V_{n,i,R,t}^1 \right) \times \mathbf{D}_i + \theta^1 \cdot \left(\ln Pollution'_{i,I,t} - \ln Pollution'_{i,R,t} \right) \times \mathbf{D}_i + \delta_{c(i)} \times \mathbf{D}_i + e_{i,t},$$

where $\mathbf{D}_i \equiv \{D_i^{0-3}, D_i^{3-6}, D_i^{6-9}, D_i^{9-12}, D_i^{12-20}, D_i^{20-30}, D_i^{30-40}\}$ is a vector of dummy variables indicating each parcel's distance to the nearest monitoring station within its corresponding city. The coefficient vectors α^1 and θ^1 represent the estimated coefficients for fiscal revenue and pollution, respectively, within each distance bin. The ratio of these two vectors is presented in Figure 4. Standard errors, clustered at the city level, are reported in parentheses. Column (2) estimates a probit model with consistent specification.

*** p < 0.01, ** p < 0.05, * p < 0.1.