Environmental Enforcement and the Repricing of Pollution Risk*

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Abstract

We examine how the Central Environmental Protection Inspection (CEPI) reshapes the capitalization of local pollution risk in China's housing market. Using resale transactions across major Chinese cities and the staggered rollout of the CEPI, we find that properties near nationally monitored polluting facilities trade at a significant discount, and that this discount narrows substantially after the inspection. The attenuation is more pronounced where pollutants are directly observable, remediation commitments are credible, realized environmental improvements are larger, and both local governments and residents pay greater attention to environmental issues. Our results indicate that the credibility and visibility of enforcement are critical determinants of how localized environmental disamenities are priced.

JEL Classification: G12, G18, Q53, Q58, R30.

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1 Introduction

Pollution is one of the most pressing externalities in developing economies, where decades of rapid industrialization have concentrated environmental damage near residential areas. Because housing is durable, geographically immobile, and the largest asset most families own, local environmental conditions can materially affect household wealth.[1] A large hedonic literature documents that proximity to pollution sources lowers property values (e.g., Chay and Greenstone, 2005; Greenstone and Gallagher, 2008; Currie, Davis, Greenstone, and Walker, 2015). If environmental enforcement reduces pollution or makes residents believe it will be reduced, it can narrow this proximity discount. Yet almost all existing evidence comes from developed economies with established regulatory institutions, and how enforcement reshapes the capitalization of pollution risk in emerging markets where enforcement credibility has historically been weak remains an open question.

This paper examines how national environmental enforcement reshapes the capitalization of local pollution risk in China's housing market. We exploit the staggered rollout of China's Central Environmental Protection Inspection, a top-down enforcement campaign launched by the central government beginning in late 2015 and expanded nationwide through 2017.[2] Unlike routine inspections administered by local environmental bureaus, the CEPI was organized by the central government, targeted the political accountability of local leaders, opened public complaint channels, and required local governments to disclose rectification plans. These features increased both the credibility and the visibility of environmental enforcement, providing a clean setting in which to study how a shift in enforcement regime affects the pricing of localized environmental disamenities.

China offers a compelling setting to study these questions. First, its residential real

[1] Piazzesi (2025) highlights housing as one of the three major asset classes in her presidential address.

[2] The first round of inspections began with a pilot inspection in late 2015 and was followed by four batches over the next two years, covering all provinces in China. See http://www.mee.gov.cn/ywgz/zysthjbhdc/dcdt/201607/t20160719_360838.shtml (in Chinese) for details.

estate market is the largest in the world, valued at approximately $74 trillion as of 2024, and housing represents more than 70% of household wealth for Chinese families (Badarinza, Balasubramaniam, and Ramadorai, 2019), making household wealth highly exposed to any repricing of local amenities.[3] Second, before the CEPI, environmental regulation relied on decentralized enforcement, and local governments routinely subordinated environmental objectives to economic growth (Wu, Deng, Huang, Morck, and Yeung, 2014; He, Wang, and Zhang, 2020), undermining enforcement credibility and leaving residents uncertain about the future cost of living near polluting facilities. The CEPI altered this dynamic by imposing central oversight, publicly disclosing pollution problems, and mandating remediation with political accountability. If residents update their beliefs about future environmental risk in response, this revision should be reflected in housing prices.

We collect granular data on housing transactions across 21 cities from one of China's largest real estate agency platforms, covering the period from June 2014 to May 2018 and encompassing over 500,000 transactions. Each transaction is matched to the nearest nationally monitored polluting facility located within the same district. We define proximity as the negative of the distance to that facility, therefore higher values correspond to greater potential exposure to local pollution. Our empirical design exploits the staggered rollout of the CEPI across cities and the spatial variation in properties' proximity to monitored polluting facilities. The effect is identified from the spatial variation in transaction prices of properties located at different distances from the same monitored facility before and after the city's first exposure to the CEPI. This specification absorbs common city-month housing-market shocks and isolates the differential price response of properties with greater exposure to polluting facilities.

We find that proximity to monitored polluting facilities is associated with a statistically and economically significant discount in residential property values, and that this discount

[3] Please see https://impacts.savills.com/market-trends/where-are-the-worlds-most-valuable-residential-markets.html for details.

is substantially reduced following the national environmental campaign. Prior to the inspection, moving one kilometer closer to a monitored facility is associated with a 1.7% lower transaction price. The CEPI attenuates this pollution-proximity price gradient by 35%, reducing the discount associated with a one-kilometer decrease in distance to a monitored facility from 1.7% to approximately 1.1%. The implied reduction in the discount corresponds to an economically significant average increase in transaction prices of roughly RMB 21,000 (approximately USD 3,102) per kilometer after the inspection. Event-study estimates show that the repricing emerges shortly after the inspection and persists over subsequent months, with no evidence of differential pre-trends. These results are robust to alternative proximity measures, more granular fixed effects, stacked DID specifications, and alternative housing price measures.

We interpret the repricing as reflecting changes in residents' perceived environmental risk. The CEPI can shift perceived risk by revealing pollution, signaling credible enforcement, mandating remediation, and directing public attention to environmental conditions. The proximity discount should therefore narrow more when these forces are more likely to reshape residents' beliefs. We present five sets of tests consistent with this interpretation.

We first test whether the repricing depends on pollutant observability. If residents price environmental risk through perceived exposure, the CEPI should narrow the proximity discount primarily for pollutants that are visible or directly experienced. We classify monitored facilities by their main pollution category: wastewater and waste-gas facilities generate visible or sensory disamenities, whereas heavy-metal and hazardous-waste facilities pose risks that are difficult to assess without technical information. Consistent with this distinction, properties near wastewater and waste-gas facilities trade at a significant discount before the inspection, and this discount declines substantially afterward. By contrast, we find no statistically significant discount or CEPI-induced attenuation for heavy-metal and hazardous-waste facilities. This pattern suggests that the repricing operates where environmental risks

are more directly perceptible.

We next use inspection disclosure content to distinguish bad-news revelation from reassurance. As He, Wang, and Zhang (2020) show, local governments in China strategically manipulate environmental data, so centralized disclosure can reveal previously opaque risks and raise perceived exposure. At the same time, credible enforcement and remediation can reassure residents that the government has identified the problem and initiated corrective action, lowering expected future risk (Zhang, Chen, and Guo, 2018; Greenstone, He, Jia, and Liu, 2022). Using province-level measures of public complaints, penalty cases, and officials held accountable, we find that the attenuation effect is larger where the inspection uncovers fewer environmental issues. When disclosed problems are more severe, the bad-news component offsets the reassurance effect and the proximity discount does not narrow. Enforcement disclosure thus has an ambiguous capitalization effect that depends on whether it primarily reveals current risk or reduces expected future risk.

We then examine the role of remediation credibility. After CEPI feedback, provincial governments released rectification plans converting inspection findings into remediation tasks, responsible agencies, and implementation deadlines. We manually review these plans and construct city-level credibility measures based on the share of items that were near-term or already completed at the time of release. The attenuation of the proximity discount is significant only in cities with more credible plans, suggesting that residents revise down the expected cost of proximity only when remediation commitments are concrete, timely, and observable.

Furthermore, we test whether realized environmental improvements reinforce the repricing. If transaction prices reflect updated expectations about future environmental conditions, the attenuation should be strongest where actual remediation follows. We capture realized improvements with three measures: the share of monitored facilities exiting the national monitoring list between 2015 and 2018, changes in city-level water quality classifications,

and changes in the air quality index. Across all three, the attenuation of the proximity discount concentrates in cities with the largest environmental gains. This result echoes Keiser and Shapiro (2019), who show that Clean Water Act–driven water quality improvements capitalize into nearby property values, and indicates that the CEPI effect reflects tangible environmental change rather than inspection announcements alone.

Finally, we test whether policy emphasis and public attention amplify the repricing. Hirshleifer, Lim, and Teoh (2009) argue that limited attention constrains the incorporation of information into asset prices. In our setting, CEPI information should capitalize more strongly when local governments prioritize environmental governance and when residents attend more closely to pollution risks. We measure government emphasis using environment-related keyword intensity in municipal work reports, and resident attention using city-level Baidu Search Indices for pollution-related terms. The CEPI-induced attenuation is more pronounced in cities where governments devote greater emphasis to environmental governance and where residents search more intensively for pollution-related terms. This pattern is consistent with evidence that environmental and climate risks are priced more strongly when public awareness is higher (Baldauf, Garlappi, and Yannelis, 2020; Bolton and Kacperczyk, 2021).

Our paper makes three contributions. First, we provide the first evidence that a centrally led environmental enforcement campaign is capitalized into housing prices. Related work focuses on specific environmental programs, including air-quality improvements under the Clean Air Act (Chay and Greenstone, 2005), hazardous-waste cleanup under Superfund (Greenstone and Gallagher, 2008), and water-pollution reduction policies (Ge, Huang, and Shi, 2025), as well as information regimes such as real-time pollution disclosure (Barwick, Li, Lin, and Zou, 2024).[4] We study a national campaign that combines political accountability, public disclosure, and mandated rectification and show that it substantially attenuates the pollution-proximity housing discount by shifting residents' perceived environmental

[4] See also Ito and Zhang (2020), who document household demand for clean air.

risk. Second, we identify enforcement credibility as a channel through which environmental conditions are capitalized into property values. A large hedonic literature establishes that pollution exposure, environmental amenities, and risk information are reflected in housing prices.[5] We show that prices respond not only to changes in pollution levels or information provision but also to the credibility of remediation commitments, a channel that has received little attention in this strand of literature. Finally, we contribute to the growing body of work on China's housing market by demonstrating that local pollution risk and central environmental enforcement materially affect property prices.[6]

The remainder of the article is organized as follows. Section 2 describes the institutional background and develops our hypotheses. Section 3 summarizes the data and key measures. Section 4 presents the baseline empirical results. Section 5 examines the mechanisms through which the price effect operates. We conclude in Section 6.

2 Institutional Background and Hypothesis Development

This section describes the institutional setting of the Central Environmental Protection Inspection, explains why it is well suited to studying how local pollution risk is capitalized into housing prices, and develops the hypotheses that guide the empirical analysis.

[5] See, among others, Chay and Greenstone (2005), Greenstone and Gallagher (2008), Currie, Davis, Greenstone, and Walker (2015), Mastromonaco (2015), and Hino and Burke (2021). Environmental risks are also priced in other asset classes: Hsu, Li, and Tsou (2023) document a pollution premium in equities driven by environmental policy uncertainty, and Seltzer, Starks, and Zhu (2022) show that climate regulatory risk is reflected in corporate bond spreads.

[6] Related studies include Fang, Gu, Xiong, and Zhou (2016), Chen and Wen (2017), Glaeser, Huang, Ma, and Shleifer (2017), Liu and Xiong (2020), Chu, Duan, Yang, and Wang (2021), Ge, Huang, and Shi (2025), Qian, Tu, Wu, and Xu (2025), Tian and Wang (2026), Chang, Wang, and Xiong (2026), and Niu, Xiang, Yang, and Zhou (2026).

2.1 Institutional Background

China's environmental governance offers a sharp setting for studying how regulatory enforcement affects local housing markets. Although China enacted its Environmental Protection Law in 1989, enforcement through most of the high-growth era remained decentralized. Local governments were charged with implementing environmental rules, yet they simultaneously competed to attract investment, employment, fiscal revenue, and output. Because stricter enforcement imposed immediate costs on local firms and dampened local economic performance, environmental objectives were routinely subordinated to growth. This central-local tension undermined the credibility of routine local enforcement and allowed polluting facilities to operate under weak supervision.[7]

The institutional environment shifted in the mid-2010s. The revised Environmental Protection Law, effective January 1, 2015, strengthened the legal basis for enforcement, raised the penalties for noncompliance, and made local governments more directly answerable for environmental outcomes in their jurisdictions. Environmental protection also rose in central political discourse and in the evaluation of local officials. These reforms created the legal and political preconditions for a more centralized campaign, but they did not by themselves dissolve local protectionism or the information frictions that obscured which facilities were polluting and whether local governments were responding. The central government still required a mechanism to verify local implementation and firm compliance. The Central Environmental Protection Inspection was introduced to fill precisely this gap. Unlike routine inspections run by local environmental bureaus, the inspection was organized by the central government and centered on the political accountability of local leaders. Central teams entered provinces, interviewed provincial leaders, reviewed local governance records, conducted site visits, received complaints from residents, and required local governments to submit rec-

[7] The misalignment between centrally set environmental targets and the growth incentives of local officials is a recurring theme in work on Chinese environmental regulation; He, Wang, and Zhang (2020) show that this misalignment shapes how local governments enforce, or decline to enforce, central environmental rules.

tification plans. The process thus combined administrative supervision, public information disclosure, and firm-level enforcement pressure in a single campaign. Zhang, Chen, and Guo (2018) study an analogous program of central supervision and find that it increased local environmental enforcement and reduced industrial emissions, providing evidence that centralized supervision can meaningfully strengthen regulatory enforcement.

The first round began with a pilot inspection in Hebei at the end of 2015 and was rolled out nationwide in four batches through 2016 and 2017, as shown in Figure 1. During each inspection, a central team was typically stationed in a province for about one month. The team opened public hotlines and mailboxes to receive environmental complaints, investigated selected cases, and transferred verified problems to local governments for rectification. After the on-site phase, the central team issued formal feedback to the provincial government, and the province was required to disclose a rectification plan and report subsequent progress.[8] This design made the inspection visible not only to firms and officials but also to residents. We exploit the staggered timing of a city's first exposure to this first round as the enforcement event in our design.[9]

Several features separate the inspection from earlier environmental policies. It was vertically organized by the central government, which narrowed the scope for local governments to shield polluting facilities. It targeted local officials as well as firms, framing environmental problems as evidence of insufficient local governance rather than as isolated firm-level violations. It relied on public participation, allowing residents to report pollution directly to the central team, which weakened local information control and raised the salience of environmental issues. And it generated public records, including inspection feedback, rectification requirements, and reports of enforcement actions. Together, these features increased both

[8] Internet Appendix Figure IA1 provides a timeline of this process.

[9] The central government later conducted a 2018 follow-up that checked whether previously identified problems had been resolved, and launched a second round beginning in 2019. By reinforcing the requirement that local governments continue rectification, these later episodes help explain why the first-round inspection could shift expectations persistently. Our analysis nonetheless focuses on the first round, which was the initial nationwide campaign and provides the cleanest staggered regulatory event for identification; we treat the follow-up and second round as part of the institutional setting rather than as separate experiments.

the credibility and the visibility of environmental enforcement. This combination makes the inspection relevant for local housing markets. Environmental risk is highly localized: a polluting facility can affect nearby neighborhoods through air emissions, wastewater discharge, perceived health risks, and negative perceptions of the surrounding area. By publicizing pollution problems, mandating rectification, and intensifying enforcement, the inspection can change how residents assess the future cost of living near a polluting facility.

We measure local exposure to pollution risk using national key monitored polluting facilities, which are major government-monitored pollution sources with fixed locations. Their locations allow us to compare housing transactions at different distances from nearby facilities, while the staggered first-round rollout provides variation in when local housing markets were exposed to central enforcement. This setting allows us to examine whether the price discount associated with proximity to polluting facilities changes after the inspection arrives.

2.2 Hypothesis Development

We develop our hypotheses based on the idea that CEPI affects housing prices by changing residents' perceived environmental risk. In the hedonic framework of Rosen (1974), housing prices capitalize local amenities and disamenities, and environmental quality is a leading example. Chay and Greenstone (2005) show that air-quality improvements raise nearby property values, Greenstone and Gallagher (2008) use the Superfund program to value hazardous-waste risk through the housing market, and Currie, Davis, Greenstone, and Walker (2015) find that the opening of an industrial plant depresses nearby home prices. These studies imply that residents' beliefs about local environmental risk are incorporated into property values. Because national key monitored polluting facilities are major local sources of environmental risk, homes closer to them are more exposed to air emissions, wastewater discharge, perceived health risks, and negative perceptions of the surrounding area. These spatially concentrated disamenities are difficult for households to avoid after

choosing a location and should therefore be reflected in transaction prices.

Hypothesis 1. *Properties located closer to national key monitored polluting facilities sell at a discount relative to otherwise comparable properties farther away.*

The inspection can change this proximity discount by updating residents' perceived environmental risk. The net effect is theoretically ambiguous. On one hand, by revealing previously opaque pollution problems, the inspection may raise perceived risk in the short run. On the other hand, by increasing the credibility of enforcement and the expectation of remediation, it can lower expected future exposure. If the remediation-credibility effect dominates the bad-news-revelation effect, the discount on homes near polluting facilities should narrow after the inspection.

Hypothesis 2. *The inspection attenuates the housing price discount associated with proximity to national key monitored polluting facilities.*

Whether and how strongly the inspection narrows the proximity discount should depend on the conditions under which residents' perceived environmental risk is most likely to decline. We distinguish two broad forces. The first is a reduction in realized environmental disamenity: if the inspection leads to firm closure, relocation, or remediation, and if local environmental quality measurably improves, the proximity discount should narrow where these improvements are larger and where the local rectification response is credible and near-term. The second is attention and observability: for the inspection's information to be reflected in housing prices, residents must notice and process it, and local governments must act on it. The proximity discount should narrow more where the underlying pollutant is directly observable, where residents are more attentive to pollution, and where local governments place greater emphasis on environmental governance.

Hypothesis 3. *The attenuation of the proximity discount is more pronounced where realized environmental improvements are larger, where local rectification is more credible, and where*

residents and local governments pay greater attention to the environment.

3 Data and Descriptive Statistics

3.1 Housing Prices and Characteristics

We obtain a unique dataset on resale housing from one of China's largest real estate agency platforms, Lianjia, covering 30 major coastal cities from June 2014 to May 2018.[10] Lianjia maintains one of the largest proprietary housing databases in the country, covering more than one million residential transaction records across major urban areas.[11] The reliability of Lianjia transaction prices and housing characteristics has been benchmarked in prior work. For instance, Ge, Huang, and Shi (2025) show that prices and property sizes recorded by Lianjia are broadly consistent with official statistics. The dataset has been widely used in empirical studies of China's housing market. Agarwal, Li, Qin, Wu, and Yan (2020) utilize the dataset to study capital gains taxes and tax evasion in resale transactions; Zhao, Yang, and Zhang (2025) examine housing-market responses to flood events based on it; and Addoum, Cong, and Zhou (2025) analyze how extreme heat affects bargaining outcomes between buyers and sellers.

We focus on residential properties. The dataset we collected covers all the transactions involving secondhand properties that took place during our sample period. Our initial dataset comprises more than one million transactions during the sample period. Each transaction record contains detailed information on property and transaction characteristics, such as transaction prices and dates, buyer demographics, initial and final listing prices, seller holding period, unit area, number of bedrooms, floor level, building age, interior decoration

[10] Since we focus on the first-round inspection, and to avoid the influence of the look-back inspection, which begins on May 30, 2018, we restrict the sample period from June 2014 to May 2018.

[11] The platform operates via city-level subdomains. For instance, the Shanghai site (`https://sh.lianjia.com/`) illustrates the typical data structure and property information available (in Chinese).

status, window orientation, and geographic coordinates. The transaction date corresponds to the date on which the buyer and seller agree on the final price and sign the sales contract on-site. [12]

We exclude outlier transactions with unit prices above 200,000 RMB per square meter, which account for roughly 0.6% of the sample.[13] We further remove observations with extreme values in property attributes such as size and number of bedrooms.[14] We also exclude transactions with missing building age, as these primarily involve older residential communities under renovation or redevelopment, where prices are more likely influenced by redevelopment expectations rather than pollution risk exposure. We end up with a sample of 509,357 transaction records.

3.2 Distance to Polluting Facility

We identify polluting facilities from the 2015 official registry of National Key Monitored Enterprises released by the Ministry of Environmental Protection of China. This list is the last pre-inspection list before the first round of the CEPI and identifies facilities subject to intensive monitoring and reporting requirements. It classifies facilities into several pollution categories, including waste gas, wastewater, wastewater treatment, heavy metals, and hazardous waste. Figure IA3 shows an example from the official list of waste-gas facilities in Beijing, which reports each facility's administrative code, district, organization code, and name. Figure 2 shows the provincial distribution of national key monitored polluting facilities. Monitored facilities are not evenly distributed across China. Economically large coastal provinces, such as Guangdong, Jiangsu, and Shandong, host many more facilities

[12] Internet Appendix Figure IA2 provides an example of a transacted property's information in the platform.

[13] This threshold captures the commonly accepted cutoff for ultra-luxury properties, which operate in a niche market and hardly reflect typical residential demand.

[14] We identify potential outliers by conducting descriptive analyses of housing characteristics in each city (e.g., minimum and maximum values) and cross-checking them on the Lianjia platform to verify that the transaction exists and involves a residential unit before deciding on removal.

than municipalities such as Beijing and Tianjin.[15]

Using the facility names and administrative identifiers in the 2015 National Key Monitored Enterprises list, we manually geocode each monitored facility with the Gaode API. For each residential community, we compute the geodesic distance to every monitored facility in the same district and assign the community to the nearest facility. We restrict the baseline sample to communities whose nearest monitored facility is within 10 kilometers, a radius within which local environmental disamenities are more likely to be salient. Section 4.1 provides further details on this sample restriction. Because the locations of residential communities and monitored facilities are fixed in our data, the assigned distance is time-invariant over the sample period. The final matched sample contains 25,329 residential communities and 323 monitored polluting facilities.

We define *Distance to polluting facility* as the minimum distance, in kilometers, from a residential community to a monitored facility in the same district. *Proximity to polluting facility* is the negative of this distance, so that higher values indicate properties located closer to a monitored facility. We use this transformation to align with the economic interpretation: greater proximity corresponds to greater exposure to local pollution risk. As an alternative measure, *Log proximity to polluting facility* is the negative logarithm of distance measured in meters, allowing the price gradient to be steeper at very short distances. We also record the pollution category of the nearest facility and use this information to examine whether residents respond differently to pollution types that vary in salience.

3.3 Central Environmental Protection Inspection

We assign each city an inspection date based on the date on which the central inspection team first entered its province, using the official CEPI schedule published by the Ministry of

[15] Figure 1 and Figure 2 show no systematic relation between the number of monitored facilities and inspection order. This mitigates concerns that provinces with more monitored facilities were inspected earlier.

Ecology and Environment and summarized in Figure 1. The first round began with a pilot inspection in Hebei at the end of 2015 and then proceeded through four nationwide batches from 2016 to 2017. Our sample period is from June 2014 to May 2018, which brackets the staggered first-round inspections. Requiring each city to have at least 12 months of observations before and after the inspection leaves 21 cities in 15 provinces.[16]

In addition to the entry dates, the official feedback reports and provincial rectification plans provide useful information for our mechanism analysis. Feedback reports summarize the pollution problems and governance failures identified by the central inspection teams, while rectification plans translate these findings into local priorities, corrective tasks, responsible agencies, and implementation deadlines. We use these documents to measure the severity of disclosed pollution problems, the remediation actions promised by local governments, and the timing of planned implementation. These measures allow us to examine whether residents update their expectations about local environmental risk based on CEPI-related information and whether such updating is reflected in housing prices.

3.4 Descriptive Statistics

Table 1 presents summary statistics for the main variables. The baseline sample contains 509,357 housing transactions. The average transaction price is RMB 3.57 million, with a median of RMB 1.89 million. The average unit price is RMB 42,400 per square meter, while the median unit price is RMB 26,100 per square meter, reflecting the right-skewed distribution of housing prices. The average residential unit has a floor area of 84.93 square meters and is located in a building that is 13.88 years old. About 69% of transactions are in buildings with elevators. The mean floor-level category is 2.03, indicating that units are, on average, located around the middle-floor category. The mean layout category is 1.08,

[16] These cities are Langfang in Hebei; Nanjing and Suzhou in Jiangsu; Beijing; Shanghai; Chongqing; Tianjin; Dongguan, Foshan, and Guangzhou in Guangdong; Wuhan in Hubei; Xiamen in Fujian; Dalian and Shenyang in Liaoning; Changsha in Hunan; Hefei in Anhui; Chengdu in Sichuan; Hangzhou in Zhejiang; and Jinan, Yantai, and Qingdao in Shandong.

suggesting that most units have a flat layout.

The average distance to the nearest monitored polluting facility is 3.71 kilometers, with a median of 1.99 kilometers. Because proximity is defined as the negative of distance, the corresponding mean proximity measure is -3.71. These statistics indicate that a large share of transactions occur relatively close to monitored polluting facilities, allowing us to estimate how the CEPI changes the price discount associated with local pollution exposure. Detailed variable definitions are provided in the Appendix.

4 Central Environmental Protection Inspections and Housing Prices

Our objective is to examine how the CEPI changes the relationship between housing prices and proximity to national key monitored polluting facilities. In the hedonic framework, housing prices capitalize local amenities and disamenities, and proximity to a polluting facility is a leading example of a localized disamenity. Homes closer to such facilities should sell at a discount that reflects residents' perceived environmental risk from air emissions, wastewater discharge, and associated health concerns. Because perceived risk is not directly observed, we infer changes in it from changes in the housing price gradient around polluting facilities. If the CEPI reduces perceived future environmental risk by making enforcement and remediation more credible, the price discount near polluting facilities should narrow after the inspection.

4.1 Baseline Results

Because the Central Environmental Protection Inspection was rolled out across provinces at different times, we use a staggered difference-in-differences design. Following Archibong

and Annan (2017), identification comes from comparing treated cities with cities that had not yet been inspected at the same point in time. We estimate the following DID model, in which one difference is before versus after the arrival of the CEPI and the other is the price difference between otherwise comparable properties at different distances from the same monitored polluting facility:

$$\ln P_{i,t} = \beta_1 Proximity_i + \beta_2 Inspection_{i,c,t} \times Proximity_i + X'_{it}\gamma + \lambda_{f(i)} + \theta_{c(i),ym(t)} + \varepsilon_{i,t}, \quad (1)$$

where $\ln P_{i,t}$ is the log transaction price of property i transacted at date t, and t refers to the contract execution date. $Proximity_i$ is the negative distance to the nearest monitored polluting facility within the same district, so that higher values indicate closer proximity. $Inspection_{i,c,t}$ equals one for transactions after the relevant local inspection date.[17]

Following Chu, Duan, Yang, and Wang (2021) and Addoum, Cong, and Zhou (2025), we include a rich set of control variables to account for other important determinants of housing prices in China. Specifically, X_{it} includes property characteristics that affect housing prices, including size, building age, elevator access, floor level, decoration, window orientation, and layout. We include nearest-facility fixed effects, $\lambda_{f(i)}$, which absorb time-invariant differences across monitored facilities and their surrounding neighborhoods. These fixed effects address the fact that facilities are not randomly located and that neighborhoods around different facilities may differ in industrial history, local amenities, transport access, and baseline housing-market conditions. We also include city-by-year-month fixed effects, $\theta_{c(i),ym(t)}$, which absorb city-level shocks to housing demand and supply in each month, including housing-market policies, macroeconomic conditions, citywide environmental trends, and seasonal fluctuations in local housing markets.[18]

[17] We assign the inspection to the entry month if the team entered in the first half of the month and to the following month if it entered in the second half. CEPI was a nationwide campaign and all sample cities were eventually treated, untreated comparisons therefore come from cities that had not yet been inspected in a given month.

[18] Because these fixed effects are monthly, they also absorb quarterly seasonality in local housing markets (Ge, Huang, and Shi, 2025).

The economic intuition of equation (1) is as follows. Before the inspection, the coefficient on proximity is β_1. Because $Proximity_i$ is defined as the negative distance to the nearest monitored facility, a negative β_1 means that homes closer to a facility sell at a discount relative to otherwise comparable homes farther away. After the inspection, the coefficient becomes $\beta_1 + \beta_2$, therefore β_2 captures the change in this proximity discount. A positive β_2 indicates that the discount narrows after the inspection, consistent with residents revising downward the perceived future environmental risk of living near monitored facilities.

Table 2 reports the baseline estimates. Columns (1) to (5) gradually add property characteristics, nearest-facility fixed effects, and city-by-year-month fixed effects. Column (5) includes all control variables and both nearest-facility fixed effects and city-by-year-month fixed effects. The coefficient on *Proximity to polluting facility* is -0.17 and statistically significant, indicating that homes closer to monitored polluting facilities sell at a discount before the inspection. This estimate implies that moving one kilometer closer to a monitored facility is associated with about a 1.7% lower transaction price before the inspection.[19] This evidence is consistent with Hypothesis 1.

The coefficient of interest is the interaction between proximity and inspection. In column (5), the coefficient is 0.06 and statistically significant, indicating that the proximity discount becomes smaller after the CEPI. The post-inspection coefficient on proximity, reflected by the coefficient on *Discount*, is approximately -0.11, suggesting that nearby homes continue to sell at a discount, but the discount is attenuated after the inspection. This finding supports Hypothesis 2.

We quantify the economic magnitude at two levels. On a per-kilometer basis, the inspection reduces the pre-inspection proximity discount by about 35% (=0.06/0.17). At the average transaction price of RMB 3.57 million in Table 1, the pre-inspection discount associated with moving one kilometer closer to a monitored facility is about RMB 61,000,

[19] The proximity measure is the negative distance to the nearest monitored facility, divided by 10 for ease of presentation.

and the CEPI attenuates this discount by about RMB 21,000 per kilometer. In cumulative terms, a property at the sample mean distance of 3.71 kilometers is 6.29 kilometers closer to a monitored facility than a property at the 10-kilometer sample boundary, where the pollution discount is negligible. Applying the per-kilometer attenuation across this distance, the estimated price recovery for a property at the mean distance is about 3.8%, equivalent to roughly RMB 135,000 at the average transaction price.[20]

A concern with staggered DID designs is that two-way fixed effects may combine treatment effects across cohorts in ways that are difficult to interpret when treatment effects are heterogeneous over time. To address this concern, column (6) reports a stacked DID specification following Cengiz, Dube, Lindner, and Zipperer (2019), in which each treated cohort is matched to not-yet-treated cities.[21] The stacked DID estimate remains positive and statistically significant, with a coefficient of 0.03 on the interaction term. This result confirms that the attenuation of the proximity discount is not driven by the TWFE comparison structure.

These findings are consistent with the hedonic evidence that housing markets capitalize environmental quality and local environmental risk. Chay and Greenstone (2005) show that air-quality improvements are reflected in property values, Greenstone and Gallagher (2008) use housing prices to value hazardous-waste risk, and Currie, Davis, Greenstone, and Walker (2015) show that toxic plant openings depress nearby home prices. Our setting differs in that the CEPI does not directly move households or facilities at the inspection date. Instead, the estimated repricing is consistent with residents revising downward the perceived future environmental risk of living near monitored facilities once central enforcement and remediation become more credible.

[20] The calculation is $(10-3.71)\times(0.06/10)\times 3.5749$ million RMB $= 135,000 RMB$, where 10 is the largest distance to the nearest polluting facility, 3.71 is the mean distance, the division by 10 reflects the scaling of the proximity variable, 0.06 is the interaction coefficient in column (5) of Table 2, and RMB 3.5749 million is the average transaction price in Table 1.

[21] The stacked DID design contains more observations because it reuses observations across cohorts: each treated cohort is matched to its own control group, and the same transaction may enter multiple stacks. In the stacked specification, both the nearest-polluting-facility fixed effects and the city-by-year-month fixed effects are interacted with stack-specific event indicators.

Figure 3 reports the event-study estimates for the six months before and twelve months after the inspection, comparing properties in the closest 25% of the distance distribution with those in the farthest 25% around the local inspection month. The pre-inspection coefficients are close to zero and statistically indistinguishable from the omitted month, suggesting no differential pre-trend between near and far properties before the inspection. After the inspection, the coefficients become positive in the second month and remain elevated for several months. Given the baseline evidence that properties closest to monitored facilities sell at a discount relative to those farthest away, this pattern is consistent with the parallel-trends assumption and with the result that the inspection narrows the near-far price gap.

4.2 Nonlinear Estimates

The baseline specification imposes a linear relation between housing prices and distance to the nearest monitored facility. Figure 4 relaxes this restriction by replacing the continuous proximity measure with one-kilometer distance-bin indicators, using the 9-10 kilometer bin as the base group. The blue dashed line reports the coefficients on the distance-bin indicators, and the red solid line reports the coefficients on the interactions between the post-inspection indicator and the distance-bin indicators. The bars denote 95% confidence intervals.

Consistent with the baseline estimates, the pre-inspection coefficients are negative for properties located close to monitored facilities and become less negative as distance increases. The discount is largest in the closest distance bins (e.g., the 0-1 km bin) and is smaller near the outer bins (e.g., the 8-9 km bin), indicating that the pollution-related price discount is concentrated near monitored facilities. The post-inspection interaction coefficients are positive across distance bins and are largest for properties closest to monitored facilities. Thus, the inspection narrows the price gap between near and far properties, but the change is not uniform across distance. The relative repricing is strongest for homes located closest to monitored facilities, where perceived pollution exposure is likely to be most salient.

4.3 Robustness Tests

We conduct several investigations to assess the robustness of the baseline results. First, Table 3 considers alternative fixed effects and alternative proximity measures. The estimated interaction between proximity and inspection remains positive and statistically significant when we replace city-by-year-month fixed effects with district-by-year-month fixed effects and when we include community fixed effects. These specifications address the concern that the baseline results are driven by time-varying local housing-market conditions or by persistent differences across residential communities. Table 3 also uses the negative logarithm of distance as an alternative measure of proximity. The interaction coefficients remain positive and significant, indicating that the results are not sensitive to the form used to measure proximity.

Second, Table 4 uses alternative housing price measures. Columns (1) and (2) use log unit transaction prices, while columns (3) and (4) use log listing prices. The interaction between proximity and inspection remains positive and statistically significant in both the two-way fixed effects (TWFE) and stacked DID specifications. The unit-price results show that the baseline effect is not mechanically driven by differences in property size. The listing-price results indicate that sellers also incorporate CEPI-related information into asking prices, consistent with the interpretation that the inspection changes the perceived environmental cost of living near monitored facilities.

Third, Tables IA1 and IA2 repeat these robustness tests using unit prices and listing prices, respectively. The coefficients on the interaction between proximity and inspection remain positive and statistically significant across these specifications. These results show that the attenuation of the proximity discount is robust across both transaction-based and listing-based price measures.

Finally, Table IA3 examines communities whose nearest monitored facility is located

between 10 and 15 kilometers away. The estimated proximity discount and its post-inspection change are not significant in this subsample. This finding supports our baseline sample restriction to communities within 10 kilometers of the nearest monitored facility and is consistent with the idea that the environmental disamenity is local.

5 Channels and Mechanisms

The baseline results establish that CEPI attenuates the housing price discount associated with proximity to monitored polluting facilities. In this section, we examine the channel through which this attenuation effect operates. Our interpretation is that CEPI changes residents' perceived environmental risk, and that this risk-perception channel operates through several distinguishable mechanisms: the salience of the pollutant, information revealed through inspection feedback, the credibility of expected remediation, realized improvements in environmental quality, and the attention of local governments and residents.

5.1 Pollutant Salience

Residents do not observe all pollution risks equally well. Some pollutants generate visible or directly experienced local disamenities; for example, air emissions produce haze and odor, and wastewater discharges discolor rivers and canals. Others, such as heavy-metal contamination or hazardous-waste storage, are harder for households to evaluate without technical information. This distinction matters because local environmental risks are capitalized into property values only to the extent that buyers recognize and price them.[22] In a closely related Chinese setting, Barwick, Li, Lin, and Zou (2024) show that the introduction of real-time air

[22] Currie, Davis, Greenstone, and Walker (2015) show that toxic plant openings reduce nearby housing prices. Banzhaf and Walsh (2008) demonstrate that households sort across neighborhoods in response to environmental quality. Graff Zivin and Neidell (2013) document that behavioral responses to pollution are conditional on its observability.

quality monitoring altered residential sorting and housing prices, with effects concentrated where the disclosed information was most salient to daily experience. If the CEPI effect operates through perceived risk, we expect it to be concentrated among pollution categories that generate more directly observable disamenities.

Columns (1) to (4) of Table 5 report subsample estimates based on the pollution category of the nearest monitored facility: heavy metals, hazardous waste, wastewater, and waste gas, respectively. The pre-inspection discount is concentrated in columns (3) and (4). The coefficient on *Proximity to polluting facility* is -0.15 for wastewater facilities ($t = -8.98$) and -0.35 for waste-gas facilities ($t = -10.01$). In contrast, the coefficients for heavy metals and hazardous waste are statistically insignificant.

The inspection-related attenuation effect follows a similar pattern. For wastewater facilities, the coefficient on *Proximity to polluting facility* $\times$ *Inspection* is 0.05 ($t = 5.21$), indicating that the CEPI offsets roughly one-third of the pre-inspection discount. For waste-gas facilities, the interaction coefficient is positive but not statistically significant. This weaker post-inspection precision may reflect the greater temporal volatility of air pollution, which makes residents' assessment of sustained improvement noisier than for visible wastewater remediation. For heavy metals and hazardous waste, the interaction terms are small and statistically insignificant.

These results suggest that the alleviation effect of CEPI is not a mechanical response to the presence of any monitored facility. It is concentrated where pollution is more likely to be observed, discussed, and incorporated into residents' perceived exposure. This evidence contributes to the environmental capitalization literature by showing that the pricing of regulatory enforcement depends not only on objective exposure, but also on the salience of the underlying pollutant. Mastromonaco (2015) finds that the housing price response to hazardous-waste sites depends on public information availability. Hino and Burke (2021) show that updated flood-zone designations reduce property values only where new risk in-

formation is disclosed. Our findings extend this strand of literature to a nationwide environmental enforcement campaign and show that observability shapes how enforcement shocks are capitalized into housing prices.

5.2 Inspection Feedback and Bad-News Disclosure

The CEPI also changed residents' information sets by publicly disclosing local pollution problems and the government's response. Information disclosure can affect housing prices in two opposite ways. On the one hand, it can reveal previously opaque risks and increase perceived exposure; on the other hand, it can also reassure residents that the central government has identified the problem and initiated corrective action. This dual role is especially relevant in China. He, Wang, and Zhang (2020) document that local governments strategically manipulate air pollution readings around regulatory thresholds, whereas CEPI inspections, conducted by central government teams, may override local incentives to suppress bad news. Christensen, Hail, and Leuz (2021) show that the real effects of mandatory sustainability disclosure depend on the content and credibility of the disclosed information, reinforcing the view that disclosure is not uniformly positive or negative.

To capture the severity of disclosed problems and the strength of the enforcement response, we consider three measures from the CEPI feedback reports issued by the Ministry of Ecology and Environment for each province. First, *the number of public complaints* captures the volume of pollution problems reported by residents and accepted by inspection teams. Second, *the number of penalty cases* captures administrative enforcement against polluting entities. Third, *the number of officials held accountable* captures political accountability for local environmental governance failures.[23] For each measure, cities are divided into high and low groups based on the median value of the measure.

Columns (1)-(2), (3)-(4), (5)-(6) of Table 6 report subsample estimates based on pub-

[23] Table IA4 reports the province-level counts of these measures as of the data collection cutoff date.

lic complaints, penalty cases, and officials held accountable, respectively. Across all three measures, the attenuation of the proximity discount is consistently larger and statistically significant in low-feedback cities (as in columns (2), (4), and (6)). For example, in low-complaint cities, the interaction coefficient is 0.06 ($t = 2.19$), whereas in high-complaint cities it is 0.03 and statistically insignificant ($t = 1.42$). The triple-interaction terms confirm this pattern. The coefficients on *Proximity to polluting facility* $\times$ *Inspection* $\times$ *High* are -0.04 ($t = -3.00$) for complaints, -0.07 ($t = -3.17$) for penalty cases, and -0.04 ($t = -2.78$) for officials held accountable.

These results indicate that stronger disclosure does not necessarily generate a larger reduction in the proximity discount. When the inspection reveals more extensive violations, the bad-news component of disclosure offsets the positive signal from remediation. In cities where fewer problems are uncovered, the reassurance effect is more likely to dominate and the proximity discount narrows. This interpretation is consistent with Jin and Leslie (2003), who show that the value of disclosure depends on the gap between prior beliefs and disclosed outcomes.

5.3 Credibility of Rectification Plans

If residents believe that identified pollution problems will be corrected soon, the expected future cost of living near monitored facilities should decline and the proximity discount should narrow. Rectification plans, released by provincial governments after CEPI feedback, translate inspection findings into concrete remediation tasks with responsible agencies and implementation deadlines. The credibility of these plans provides a useful proxy for residents' expectations about the pace of environmental improvement.[24]

[24] A broader literature documents that environmental regulation produces real outcomes primarily when enforcement is credible. Greenstone and Hanna (2014) show that the Clean Air Act and Clean Water Act improved environmental quality, with effects depending on enforcement stringency. Greenstone, He, Jia, and Liu (2022) provide directly relevant evidence from China, showing that continuous emissions monitoring systems improved regulatory compliance, but only where monitoring data were credibly linked to enforcement.

We consider two measures from provincial rectification plans. We manually count each rectification item in the plans released after CEPI feedback and assign each item to the city affected by the required action. *Short-term remediation share* is the city-level share of rectification items that had been completed, required immediate action, or had deadlines within six months when the plan was released. *Completed-at-release share* is the city-level share of items already completed at the time of plan release. These measures capture whether local remediation was credible, observable, and near-term.

Empirically, we separate the sample into high- and low-credibility groups using the median of each proxy. Columns (1) to (4) of Table 7 report estimates by the credibility and timing of remediation commitments. We find that the attenuation is concentrated in cities with higher values of both measures. The triple-interaction coefficient is 0.09 ($t = 3.60$) for the short-term remediation share and 0.10 ($t = 3.42$) for the completed-at-release share. In high-credibility cities, the inspection interaction is positive and statistically significant, while we observe no significant attenuation effect in low-credibility cities. These results indicate that the inspection attenuates the proximity discount only when local follow-up plans make remediation credible. Concrete, timely, and observable commitments appear necessary for residents to revise downward the expected future cost of living near monitored facilities.

5.4 Realized Environmental Improvements

The risk-perception channel implies that realized improvements in local environmental conditions should reinforce the attenuation of the proximity discount. If the CEPI-related price response reflects updated expectations about future environmental quality, those expectations should be validated when actual remediation occurs. The hedonic literature confirms

Duflo, Greenstone, Pande, and Ryan (2013) demonstrate that randomized inspections in Gujarat substantially reduced emissions. Gray and Shimshack (2011) show that the deterrence effect of inspections depends on the probability of follow-up enforcement. In financial markets, Seltzer, Starks, and Zhu (2022) show that climate regulatory risk is priced in corporate bonds based on the perceived credibility and stringency of commitments rather than announcements alone.

that environmental quality changes are capitalized into property values.[25]

We first use removal from the National Key Monitored Enterprises list as a proxy for realized remediation. We begin with the 2015 list of monitored facilities and compare it with the 2018 list. For each city, *monitoring-list exit share* is the fraction of facilities on the 2015 list that no longer appear on the 2018 list. A higher exit share can reflect facility closure, relocation, emission reduction below the monitoring threshold, or other forms of regulatory cleanup.

Table 8 shows that the attenuation of the proximity discount is larger in cities with a higher monitoring-list exit share. In the median split, the coefficient on *Proximity to polluting facility* $\times$ *Inspection* is 0.06 and statistically significant in high-exit cities, compared with 0.03 and insignificant in low-exit cities. The triple-interaction coefficient is 0.02 and statistically significant. The result is similar when comparing the top and bottom 30% of the exit-share distribution.

We interpret monitoring-list exit as evidence that a facility has likely completed the required rectification or reduced emissions sufficiently to no longer meet the criteria for national key monitoring. Such exit may reflect the adoption of cleaner energy, upgrades in pollution-control equipment, improvements in production technology, or other compliance actions that lower regulated emissions. At the same time, list exit is an administrative indicator rather than a direct measure of ambient pollution exposure. For this reason, we provide complementary evidence with direct measures of local environmental quality in the following part.

We measure water quality improvement using changes in city-level water quality classifications reported by municipal Ecology and Environment Bureaus from 2015 to 2018. We

[25] Chay and Greenstone (2005) show that air-quality improvements induced by the Clean Air Act raised housing values by approximately 0.2–0.4% per 1% reduction in particulates. Gamper-Rabindran and Timmins (2013) find that Superfund cleanups generate positive housing price effects. Bento, Freedman, and Lang (2015) demonstrate that Clean Air Act benefits are reflected in house price appreciation.

measure air quality improvement using changes in AQI from monitoring-station data over the same period. Columns (1)-(2) and (3)-(4) of Table 9 report estimates by realized improvements in water quality and air quality. We find that the attenuation of the proximity discount is concentrated in cities with larger realized improvements. For wastewater improvement, the inspection interaction is 0.03 and statistically significant in high-improvement cities, compared with -0.01 in low-improvement cities. The triple-interaction coefficient is 0.04. For air quality improvement, the corresponding interaction is 0.15 in high-improvement cities and -0.01 in low-improvement cities, with a triple-interaction coefficient of 0.16.

Together, Tables 8 and 9 support the interpretation that the CEPI effect on housing prices is mediated by changes in actual environmental conditions, not merely by the announcement of inspections. The results echo the findings of Greenstone and Gallagher (2008), who show that Superfund site cleanups generate positive capitalization effects in nearby housing markets. More recent evidence from China reinforces this interpretation: Ito and Zhang (2020) demonstrate that Chinese households' willingness to pay for clean air responds to real-time pollution information, with larger effects in cities where air quality has measurably improved. In our context, the realized exit of facilities from the national monitoring list and the measurable improvement in local water and air quality both serve as tangible signals that inspection-driven remediation has been carried out, reinforcing the attenuation of the proximity discount.

5.5 Local Government Environmental Emphasis

The preceding results suggest that residents respond to both information and realized remediation. A remaining question is whether local governments make the inspection salient through their own policy communication. Government work reports are annual public documents that summarize past achievements and set policy priorities for the coming year. They therefore provide a useful measure of local governments' stated environmental emphasis and

planned governance priorities. This measure is closer to a policy-priority signal than to attention in the psychological sense.

We measure local government environmental emphasis using environment-related keyword intensity in municipal government work reports. Following the text-as-data approach of Baker, Bloom, and Davis (2016), we construct a dictionary of 87 terms related to environmental pollution, environmental governance, inspection, regulation, enforcement, monitoring, discharge permits, and remediation.[26] For each city-year, we count the number of dictionary terms in the government work report and divide it by the total number of Chinese, English, and numeric characters, multiplied by 10,000. This normalization makes the measure comparable across reports of different lengths.

Figure 5 plots the aggregate trend from 2014 to 2023. Both the raw frequency of environment-related keywords and the intensity per 10,000 characters begin to rise during the first round of CEPI and increase more sharply in the following year.[27] This pattern suggests that local governments began to place greater emphasis on environmental governance during the inspection period, with the shift becoming more visible in subsequent work reports. Internet Appendix Figure IA4 provides a more granular heatmap of the top 15 keywords. Terms related to environmental inspection, pollution control, regulation, and enforcement increase during and after the inspection period, consistent with local governments incorporating CEPI-related priorities into formal policy communication.

Table 10 examines whether local government environmental emphasis strengthens the CEPI effect. Columns (1) and (2) split cities by the pre-inspection level of environmental emphasis, measured using the 2015 government work report. Columns (3) and (4) split cities by the change in emphasis from the 2015 report to the first post-inspection report.

[26] Gentzkow, Kelly, and Taddy (2019) provide a comprehensive discussion of text-as-data methods in economics. Hassan, Hollander, van Lent, and Tahoun (2019) extend this approach to the firm level by constructing text-based measures of political risk exposure from earnings-call transcripts.

[27] Government work reports are typically released at the beginning of each year. Thus, the content of the 2018 report may reflect local government work and CEPI-related developments that occurred in 2017.

The triple-interaction coefficient is 0.05 ($t = 4.34$) for the pre-inspection level and 0.09 ($t = 3.56$) for the post-inspection change. These estimates indicate that the attenuation of the proximity discount is stronger where local governments place greater emphasis on environmental governance, especially where this emphasis rises after the inspection. Such emphasis serves as a local policy signal that makes CEPI-related remediation more credible to the housing market.

5.6 Residents' Environmental Concern

We next examine whether residents' own environmental concern strengthens the CEPI effect. If the inspection changes perceived environmental risk, the price response should be larger where residents are more likely to notice and process pollution-related information.

Following the approach of Choi, Gao, and Jiang (2020), we measure residents' environmental concern using city-level Baidu Search Indices for two keywords: *smog* and *environmental pollution*. The indices are scaled by city population to make search intensity comparable across cities. We also construct the first principal component of the two population-scaled indices as a summary measure of environmental concern. These measures capture whether local residents actively search for pollution-related information and are therefore more likely to update beliefs when CEPI-related information becomes available.

Columns (1) to (6) of Table 11 report estimates by residents' environmental concern. Columns (1) and (2) split cities by the Baidu Search Index for smog, columns (3) and (4) by the Baidu Search Index for environmental pollution, and columns (5) and (6) by the first principal component of the two indices. Within each pair, the first column reports estimates for high-concern cities and the second for low-concern cities. Across all three measures, the attenuation of the proximity discount is concentrated in high-concern cities. The triple-interaction coefficients are 0.02 for smog ($t = 2.51$), 0.07 for environmental pollution ($t = 5.24$), and 0.02 for the principal component ($t = 2.23$).

The evidence on residents' attention complements the government attention results. Together, they indicate that the CEPI signal is more strongly capitalized when both government responsiveness and resident awareness are active. This dual-attention mechanism is consistent with the theoretical prediction of Hirshleifer, Lim, and Teoh (2009) that limited attention constrains the incorporation of information into asset prices. Recent work reinforces this view: Giglio, Maggiori, Rao, Stroebel, and Weber (2021) argue that attention frictions are a leading explanation for why some environmental risks remain underpriced, and Bolton and Kacperczyk (2021) show that the pricing of carbon emissions in equity markets has strengthened as institutional attention to climate risk has risen.

Overall, the mechanism results present a coherent picture. The CEPI affects housing prices by changing perceived environmental risk. The effect is concentrated where pollution is salient, remediation is credible and timely, disclosed problems do not overwhelm the reassurance signal, realized environmental improvements occur, and both local governments and residents pay attention to environmental issues.

6 Conclusion

This paper examines whether centralized environmental enforcement changes the capitalization of local pollution risk in China's housing market. Using transaction-level resale housing data across major Chinese cities and the staggered rollout of the Central Environmental Protection Inspection, we find that residential properties closer to nationally monitored polluting facilities trade at a significant discount before the inspection, and that this discount narrows substantially afterward.

We interpret this repricing through the channel of residents' perceived environmental risk. The attenuation of the proximity discount is concentrated where pollutants are directly perceptible to residents, where rectification commitments are credible and near-term, where

disclosed violations do not dominate the reassurance signal, where realized improvements in environmental quality are larger, and where local governments and residents pay greater attention to pollution risks. Each of these patterns points to the same underlying force: credible central enforcement leads residents to revise downward the expected future cost of living near monitored polluting facilities, and this belief revision is reflected in transaction prices.

Our findings highlight the importance of credibility and visibility in environmental enforcement. A top-down inspection campaign that combines political accountability, public disclosure, and mandated remediation can reshape how households value proximity to pollution sources, even without directly relocating residents or immediately closing facilities. For housing market participants, the results indicate that proximity to polluting facilities is a priced risk factor that responds to shifts in the enforcement regime, underscoring the importance of incorporating regulatory credibility into property valuation. More broadly, our evidence demonstrates that credible environmental governance can improve household welfare through an asset-price channel, complementing the direct health and amenity benefits of pollution reduction.

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Appendix: Variable Definitions

This table reports the name, description, frequency, and source of variables used in this study.

Name	Description	Observation level	Source
Housing Transactions			
Transaction price	Transaction price of house i at deal date t (RMB).	Property	Lianjia
Listing price	Listing price of house i at deal date t (RMB).	Property	Lianjia
Unit price	Transaction price per square meter of house i at deal date t (RMB).	Property	Lianjia
Property Attributes			
Number of bedrooms	Number of bedrooms of a property.	Property	Lianjia
Size	Size of a property.	Property	Lianjia
Age	Difference between the transaction year and the year the property was built.	Property	Lianjia
Floor level	Categorical variable equal to 1 for low floors, 2 for middle floors, and 3 for high floors.	Property	Lianjia
Decoration	Categorical variable equal 1 for 'Other', 2 for 'No decoration', 3 for 'Basic decoration', and 4 for 'Intensive decoration'.	Property	Lianjia
Elevator	Dummy equal to 1 if the house has an elevator, and 0 otherwise.	Property	Lianjia
Window orientation	Dummy variable equal to 1 if the window faces south, and 0 otherwise.	Property	Lianjia
Layout	Categorical variable for unit layout structure, coded as 1 for flat, 2 for loft, 3 for duplex, 4 for split-level, 5 for staggered-level, and 6 for hybrid duplex/split-level units.	Property	Lianjia
Distance to Polluting Facility Exposure and Inspection			
Distance to polluting facility	Distance to the nearest polluting facility within the same district (km).	Property	Manually calculated
Proximity to polluting facility	The negative value of distance to the nearest polluting facility within the same district (km).	Property	Manually calculated
Log proximity to polluting facility	The negative logarithm of the distance from a community to its nearest polluting facility within the same district (m).	Property	Manually calculated
Inspection	Indicator equal to one for transactions occurring after the relevant central environmental inspection date.	City	The Ministry of Ecology and Environment.

Continued on next page

Appendix: Variable Definitions-Continued

Name	Description	Observation level	Source
Mechanism Variables			
Number of Complaints	Total number of public environmental complaints received and accepted by the central environmental inspection team during the inspection period.	Province	The Ministry of Ecology and Environment.
Penalty Cases	Number of cases filed for administrative penalty against polluting entities during the inspection period, as reported in post-inspection releases by the Ministry of Ecology and Environment.	Province	The Ministry of Ecology and Environment.
Officials Held Accountable	Number of officials held accountable for environmental governance failures following the inspection, as reported in post-inspection releases by the Ministry of Ecology and Environment.	Province	The Ministry of Ecology and Environment.
Short-term Remediation Share	Share of rectification items that had already been completed, required immediate rectification, or had deadlines within six months when the rectification plan was released.	City	The Ministry of Ecology and Environment.
Completed-at-release Share	Share of rectification items that had already been completed at the time the rectification plan was released.	City	The Ministry of Ecology and Environment.
Monitoring-List Exit Share	Share of firms included in the 2015 National Key Monitored Enterprises list that no longer appear in the 2018 list.	City	National Key Monitored Enterprises
Wastewater Improvement	Improvement in city-level water quality from 2015 to 2018, based on water quality classifications reported by municipal Ecology and Environment Bureaus.	City × Month	Municipal Ecology and Environment Bureaus
Air Quality Improvement	Improvement in air quality from 2015 to 2018, measured using AQI data from air-quality monitoring stations.	Station × Month	Municipal Ecology and Environment Bureaus
Government Environmental Emphasis	Number of environment-related keywords per 10,000 characters in municipal government work reports. The keyword dictionary covers terms related to environmental pollution, governance, inspection, regulation, enforcement, monitoring, and discharge permits.	City × Year	Municipal government work reports
Smog	City-level Baidu Search Index for the keyword *smog*, averaged across months in 2015 and scaled by city population.	City	Baidu Index
Environmental Pollution	City-level Baidu Search Index for the keyword *environmental pollution*, averaged across months in 2015 and scaled by city population.	City	Baidu Index
Principal Component	First principal component of the population-scaled Baidu Search Indices for *smog* and *environmental pollution*.	City	Manually calculated

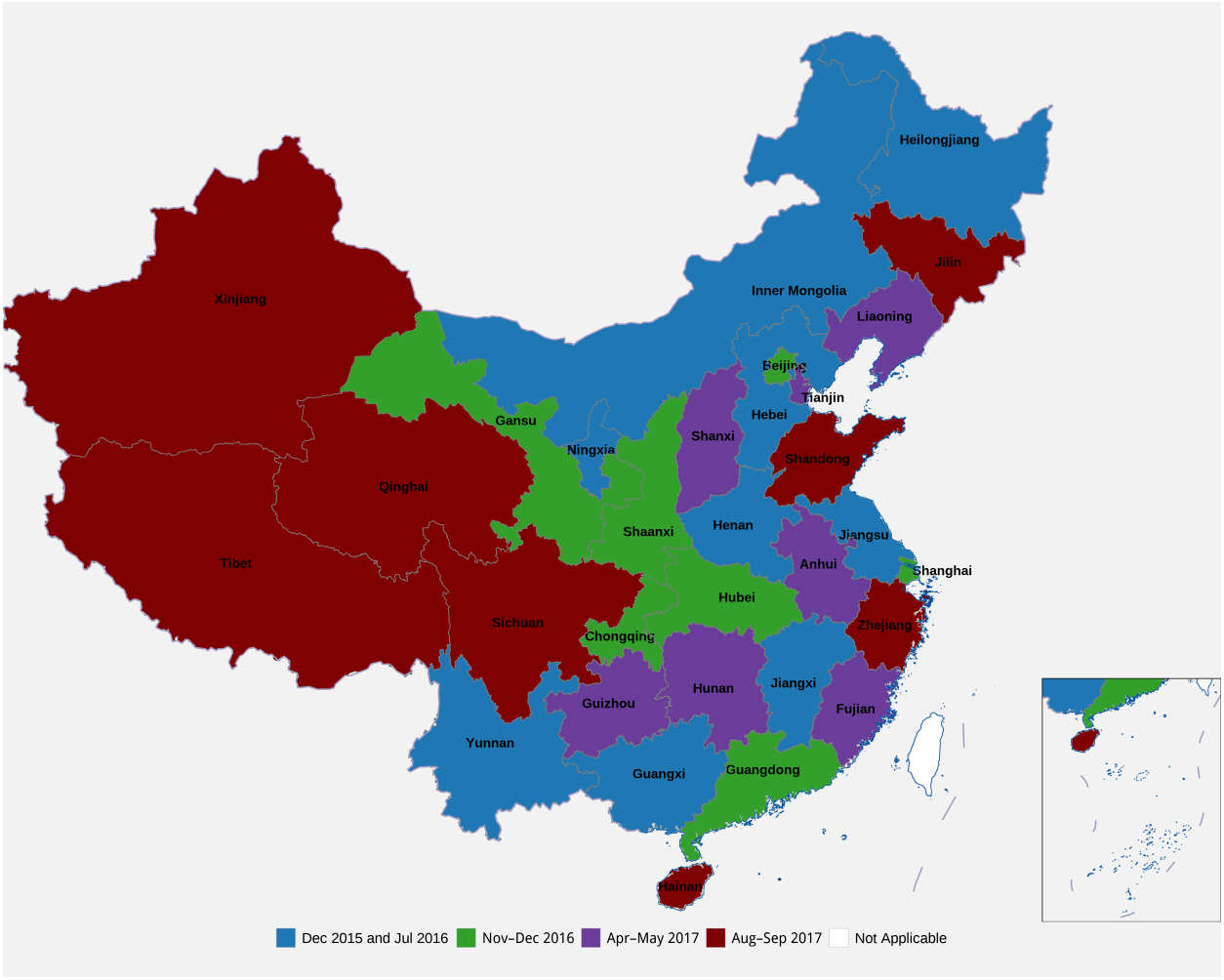


Figure 1 Rollout of the First-Round Central Environmental Protection Inspections

This figure shows the provincial rollout of the first round of Central Environmental Inspections. The inspection began with a pilot in Hebei in December 2015. The first batch, launched in July 2016, covered Ningxia, Inner Mongolia, Jiangxi, Guangxi, Jiangsu, Yunnan, Henan, and Heilongjiang. The second batch, launched in November 2016, covered Chongqing, Hubei, Shanghai, Guangdong, Shaanxi, Beijing, and Gansu. The third batch, launched in April 2017, covered Fujian, Hunan, Liaoning, Guizhou, Anhui, Tianjin, and Shanxi. The fourth batch, launched in August to September 2017, covered Jilin, Zhejiang, Shandong, Hainan, Sichuan, Tibet, Qinghai, and Xinjiang. Provinces are shaded according to their inspection time, as indicated in the legend.

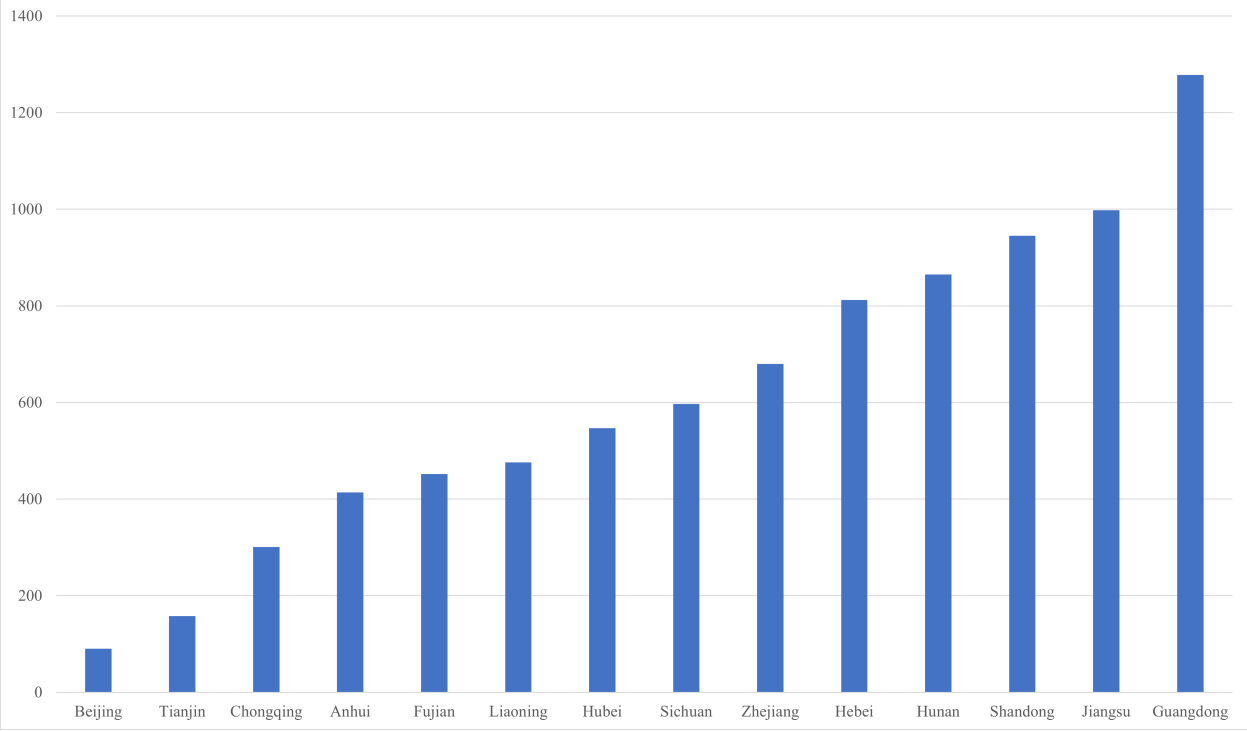


Figure 2 National Key Monitored Polluting Facilities by Province

This figure reports the number of national key monitored polluting facilities by province. These facilities are identified from the official 2015 list released by the Ministry of Environmental Protection of the People's Republic of China. The full list covers multiple categories, including waste gas, wastewater, wastewater treatment plants, heavy metals, and hazardous waste.

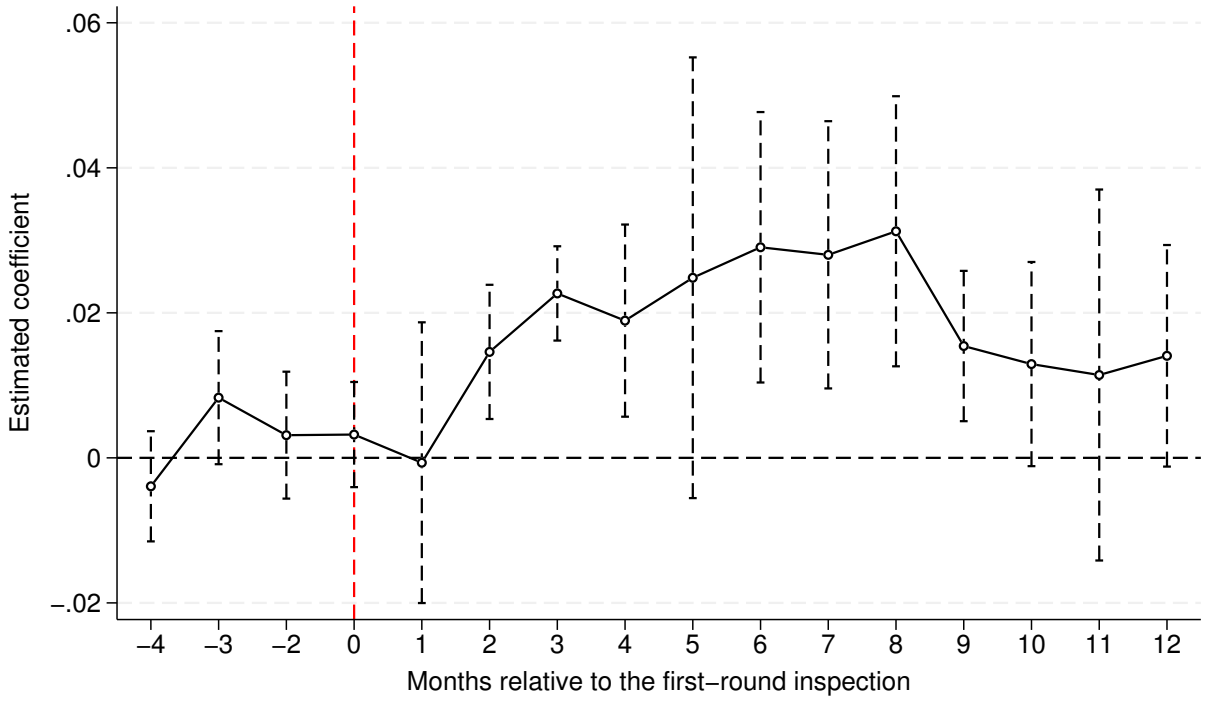


Figure 3 Event Study Around the Environmental Protection Inspections

This figure illustrates the dynamic housing market response around the first-round central environmental protection inspections. Specifically, it plots the estimated coefficients β_k and the corresponding 95% confidence intervals estimated from the following event-study specification:

$$\ln P_{ict} = \beta_0 + \sum_{\substack{k=-4 \\ k\neq -1}}^{12} \beta_k \left(Treat_i \times Inspection_{ct}^k \right) + X_{it}'\gamma + \lambda_{f\times e} + \theta_{cym} + \varepsilon_{ict},$$

where i denotes property, c denotes city, and t denotes month. The dependent variable, $\ln P_{ict}$, is the log transaction price. $Treat_i$ equals one for properties in the bottom quartile of distance to the nearest polluting facility within the same district, corresponding to the closest 25% of properties, and zero for properties in the top quartile of distance, corresponding to the farthest 25% of properties. $Inspection_{ct}^k$ is an event-time indicator equal to one if month t is k months relative to city c's inspection month. We consider $k \in \{-4, \ldots, 12\}$, with event month -1 omitted as the reference period. X_{it} denotes property-level controls, $\lambda_{f\times e}$ denotes the nearest polluting facility$\times$ event fixed effects, and θ_{cym} denotes the city$\times$ year-month$\times$event fixed effects. The sample period covers the first-round inspection and runs from June 2014 to June 2018.

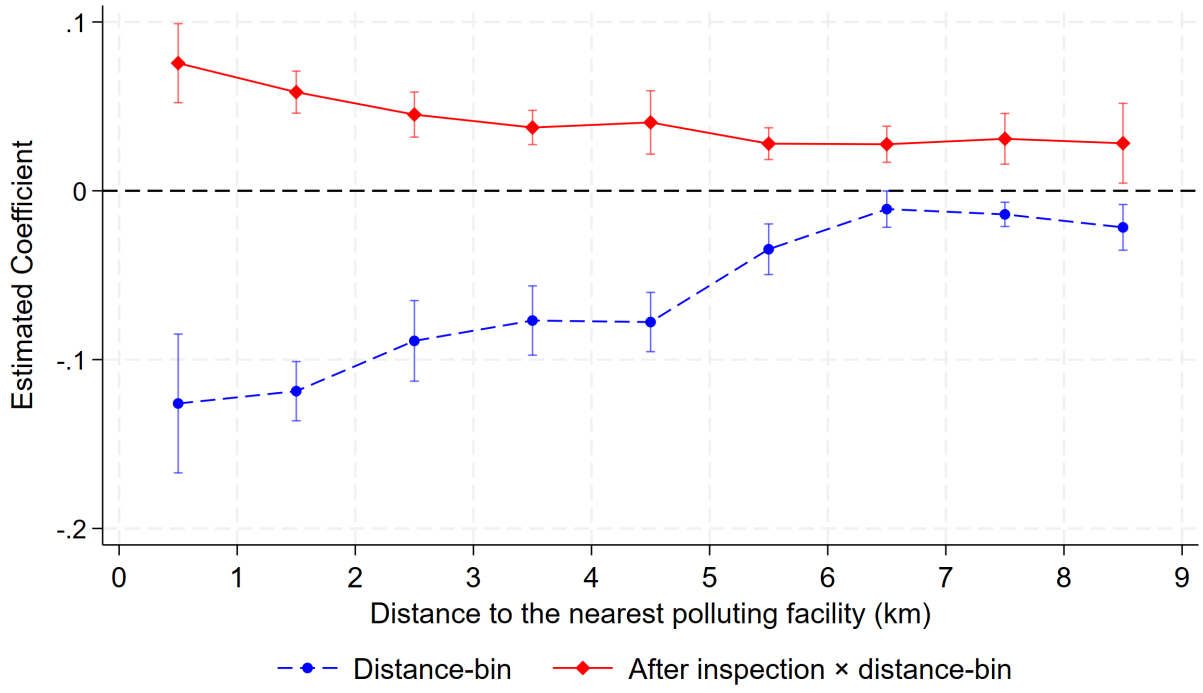


Figure 4 Housing Price Gradient by Distance to Polluting Facilities

This figure plots the estimated pollution-related housing price discount by distance to the nearest polluting facility for the first-round inspection. Distance is grouped into one-kilometer bins from 0 to 10 kilometers, with the 9 to 10 kilometer bin omitted as the reference group. The blue dashed line reports the coefficients on the distance-bin indicators, while the red solid line reports the coefficients on the interactions between the post-inspection indicator and the distance-bin indicators. The sample covers the period from June 2014 to June 2018. Controls and fixed effects are included as in the baseline specification. Vertical bars denote 95% confidence intervals.

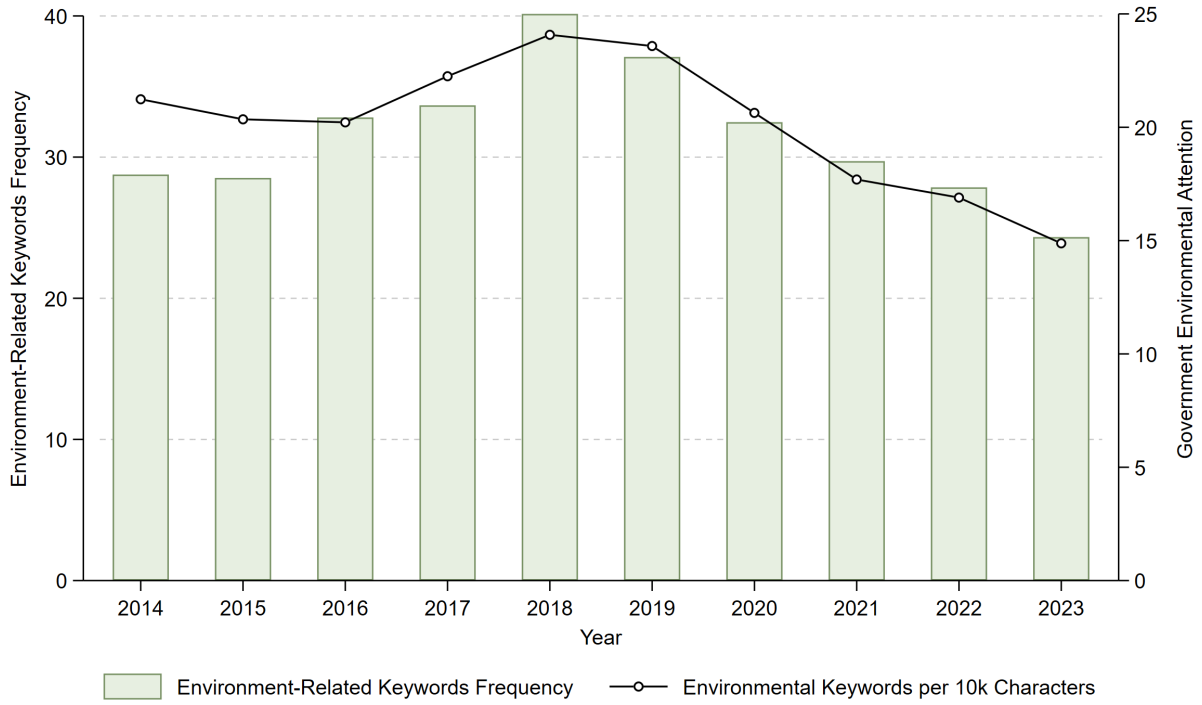


Figure 5 Local Government Environmental Attention in Work Reports

This figure plots the frequency of environment-related keywords per 10,000 characters in municipal government work reports. Keywords cover environmental pollution, environmental governance, inspection, regulation, enforcement, monitoring, and discharge permits. Government work reports are typically released in the first two months of the year. The sample covers 2014 to 2023.

Table 1 Summary Statistics

This table reports summary statistics for the main variables used in the analysis, including the number of observations, mean, median, standard deviation, minimum, and maximum. The sample period is 2014 to 2018. Continuous variables are winsorized at the 1st and 99th percentiles. Detailed variable definitions are provided in Appendix.

	N	Mean	Median	*SD*	Minimum	Maximum
Transaction price (10,000 RMB)	509,357	357.49	189	249.88	42	1,400
Listing price (10,000 RMB)	401,628	339.93	178	230.62	42	1,260
Unit price (10,000 RMB/m^2)	509,357	4.24	2.61	2.24	0.65	10.93
Size	509,357	84.93	59.96	33.93	31.03	224.11
Age	509,357	13.88	8	7.85	2	36
Floor level	509,357	2.03	1	0.74	1	3
Decoration	509,357	2.98	2	1.20	1	4
Elevator	509,357	0.69	0	0.46	0	1
Window orientation	509,357	0.34	0	0.47	0	1
Layout	509,357	1.08	1	0.47	1	5
Inspection	509,357	0.39	0	0.49	0	1
Distance to polluting facility (km)	509,357	3.71	1.99	2.27	0.01	10.00
Proximity to polluting facility (km)	509,357	-3.71	-1.99	2.27	-10.00	-0.01
Proximity to polluting facility (log, m)	509,357	-8.00	-8.52	0.72	-9.21	-2.64

Table 2 Environmental Inspections and the Pollution-Related Housing Discount

This table reports baseline estimates of how housing prices vary with proximity to the nearest polluting facility and how this relationship changes after central environmental protection inspections. The dependent variable is the log transaction price, $\ln(P_{i,t})$. *Proximity to polluting facility* is the negative distance from a community to its nearest polluting facility within the same district, divided by 10 for ease of presentation; thus, higher values indicate closer proximity to a polluting facility. *Inspection* equals one for transactions after the relevant inspection date. Columns (1) to (5) report estimates from the baseline DID specifications. Column (6) reports estimates from a stacked DID specification, in which each treated group is matched to a corresponding control group and the nearest-polluting-facility and city-by-year-month fixed effects are interacted with stack indicators. Because the same observations may enter multiple matched treatment-control stacks, the number of observations in column (6) is larger than in the other columns. Controls and fixed effects are included as indicated. *t*-statistics based on city-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Proximity to polluting facility	-0.07	-0.08	-0.17***	-0.21***	-0.17***	-0.14***
	(-0.49)	(-0.92)	(3.31)	(-6.83)	(-9.22)	(-3.25)
Proximity to polluting facility ×	-0.43	-0.47**	-0.83***	0.02	0.06***	0.03***
Inspection	(-1.70)	(-2.61)	(-19.56)	(0.85)	(12.44)	(3.53)
Discount	-0.51	-0.55	-0.67	-0.18***	-0.11***	-0.10***
	(-1.36)	(-4.49)	(-11.37)	(-3.41)	(-6.24)	(-3.07)
Size		0.01***	0.01***	0.01***	0.01***	0.01***
		(16.77)	(28.82)	(26.04)	(23.00)	(23.86)
Age		0.03**	-0.01	0.01***	-0.04***	-0.01***
		(2.68)	(-1.01)	(11.13)	(-4.00)	(-3.29)
Orientation		-0.12	0.02**	0.01	0.02	0.01
		(-1.29)	(2.65)	(1.28)	(0.63)	(0.24)
No decoration		-0.13*	-0.06	-0.09***	-0.03***	-0.03***
		(-2.03)	(-1.36)	(-18.76)	(-12.47)	(-3.18)
Basic decoration		0.24*	-0.01	-0.04***	-0.02***	-0.02***
		(2.09)	(-0.30)	(-5.04)	(-4.47)	(-5.86)
Intensive decoration		0.35**	0.04**	0.05***	0.03***	0.04***
		(2.42)	(2.83)	(7.18)	(5.02)	(8.13)
Elevator		0.41***	0.09***	0.26***	0.07***	0.07***
		(5.38)	(13.79)	(14.28)	(11.48)	(18.76)
Middle floor		0.01**	0.04**	-0.02	0.04**	0.04**
		(2.36)	(2.47)	(-1.42)	(2.45)	(2.60)
High floor		-0.05*	-0.01	-0.01**	-0.01*	-0.01*
		(-2.04)	(-1.62)	(-2.92)	(-1.83)	(-2.09)
Layout Indicator	No	Yes	Yes	Yes	Yes	Yes
Nearest polluting facility FE	No	No	Yes	No	Yes	Yes
City×year-month FE	No	No	No	Yes	Yes	Yes
Number of observations	533,599	533,599	533,584	533,597	533,583	1,576,278
Adjusted R^2	0.023	0.427	0.848	0.818	0.910	0.929

Table 3 Alternative Proximity Measures and Fixed Effects

This table reports coefficient estimates from additional specifications. Columns (1) and (2) use the negative logarithm of distance to the nearest polluting facility as the proximity measure, divided by 10 for ease of presentation. Columns (3) and (4) estimate the baseline specification with more granular community fixed effects. Controls and fixed effects are included as indicated. The sample covers the period from June 2014 to May 2018 for the first-round inspection. t-statistics based on city-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Alternative Fixed Effects		Log of Proximity		
	(1)	(2)	(3)	(4)	(5)
Proximity to polluting facility	-0.16***		-0.45***	-0.42***	
	(-9.40)		(-6.71)	(-6.49)	
Proximity to polluting facility ×	0.05***	0.03***	0.20***	0.13***	0.13***
Inspection	(6.39)	(16.05)	(8.26)	(5.07)	(9.38)
Discount	-0.11***		-0.25***	-0.29***	
	(-5.91)		(-4.56)	(-4.96)	
Property characteristics	Yes	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	No	Yes	Yes	No
Community FE	No	Yes	No	No	Yes
City×year-month FE	No	Yes	Yes	No	Yes
District×year-month FE	Yes	No	No	Yes	No
Number of observations	533,431	528,425	533,583	533,431	528,425
Adjusted R^2	0.910	0.965	0.908	0.910	0.965

Table 4 Alternative Housing Price Measures

This table reports estimates from baseline specifications using alternative housing price measures. Columns (1) and (2) use the log unit price, while columns (3) and (4) use the log listing price. Within each pricing measure, the first column reports the two-way fixed effects (TWFE) estimate and the second column reports the stacked DID estimate. In the stacked DID specifications, each treated group is matched to a corresponding control group and the nearest-polluting-facility and city-by-year-month fixed effects are interacted with stack indicators. Because the same observations may enter multiple matched treatment-control stacks, the number of observations is larger than in the corresponding TWFE specifications. The main variable of interest is the interaction between *Proximity to polluting facility* and *Inspection*. Controls and fixed effects are included as indicated. The sample covers the period from June 2014 to May 2018 for the first-round inspection. *t*-statistics based on district-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Unit Price (RMB/m^2)		Listing Price	
	TWFE	Stacked DID	TWFE	Stacked DID
	(1)	(2)	(3)	(4)
Proximity to polluting facility	-0.19***	-0.15***	-0.17***	-0.13**
	(-9.48)	(-3.60)	(-6.91)	(-2.61)
Proximity to polluting facility ×	0.07***	0.05***	0.06***	0.03**
Inspection	(7.83)	(3.72)	(11.46)	(2.49)
Discount	-0.11	-0.10***	-0.11	-0.10**
	(-7.12)	(-3.36)	(-4.57)	(-2.58)
Property characteristics	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	Yes	Yes	Yes
City× year-month FE	Yes	Yes	Yes	Yes
Number of observations	533,583	1,576,278	401,614	1,292,294
Adjusted R^2	0.893	0.926	0.913	0.901

Table 5 Pollution Type and Nearby Housing Prices

This table reports estimates separately by the pollution category of the nearest monitored facility. The dependent variable is the log transaction price, $\ln(P_{i,t})$. *Proximity to polluting facility* is the negative distance from a residential community to its nearest monitored facility within the same district, divided by 10 for ease of presentation, higher values indicate closer proximity. Columns (1) to (4) restrict the sample to properties whose nearest monitored facility is classified as heavy metals, hazardous waste, wastewater, or waste gas, respectively. Facility categories are identified from the 2015 official list of National Key Monitored Enterprises. *Inspection* equals one for transactions after the local inspection date. All specifications include property characteristics, nearest-facility fixed effects, and city-by-year-month fixed effects. The sample period is June 2014 to May 2018. t-statistics based on district-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Heavy Metals (1)	Hazardous Waste (2)	Wastewater (3)	Waste Gas (4)
Proximity to polluting facility	-0.01	0.18	-0.15***	-0.35***
	(-0.11)	(1.33)	(-8.98)	(-10.01)
Proximity to polluting facility ×	0.03	0.10	0.05***	0.06
Inspection	(0.39)	(1.11)	(5.21)	(1.45)
Discount	0.02	0.28	-0.10***	-0.28***
	(0.30)	(1.16)	(-5.39)	(-3.64)
Property characteristics	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	Yes	Yes	Yes
City× year-month FE	Yes	Yes	Yes	Yes
Number of observations	30,161	19,759	380,477	78,832
Adjusted R^2	0.935	0.917	0.904	0.929

Table 6 Public Complaints and Enforcement Pressure

This table reports estimates for subsamples with different levels of inspection feedback and enforcement pressure. Feedback and enforcement pressure are measured by the number of public environmental complaints received and accepted by the inspection team, the number of penalty cases, and the number of officials held accountable, using official CEPI reports and post-inspection releases by the Ministry of Ecology and Environment. For each measure, cities are divided into high and low groups based on the median value of the measure. The dependent variable is the log transaction price, $\ln(P_{i,t})$. *Proximity to polluting facility* is the negative distance from a residential community to its nearest monitored facility within the same district, divided by 10 for ease of presentation, higher values indicate closer proximity. *Inspection* equals one for transactions after the local inspection date. *High* is an indicator equal to one for cities with values above the median of the corresponding measure. Property attributes and specified fixed effects are included accordingly. The sample period is June 2014 to May 2018. t-statistics based on district-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Number of Complaints		Penalty Cases		Officials Held Accountable	
	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)
Proximity to polluting facility	-0.02	-0.19***	-0.07	-0.19***	-0.01	-0.19***
	(-0.30)	(-3.41)	(-1.20)	(-3.34)	(-0.08)	(-3.41)
Proximity to polluting facility ×	0.03	0.06**	-0.02	0.06**	0.04	0.06**
Inspection	(1.42)	(2.19)	(-0.04)	(2.25)	(1.50)	(2.09)
Proximity to polluting facility ×	-0.04**		-0.07***		-0.04**	
Inspection × *High*	(-3.00)		(-3.17)		(-2.78)	
Property characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	Yes	Yes	Yes	Yes	Yes
City× year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	74,581	434,760	94,005	415,336	79,394	429,947
Adjusted R^2	0.833	0.856	0.854	0.852	0.833	0.853

Table 7 Credibility of Rectification Plans

This table reports estimates for subsamples that differ in the timing of remediation commitments in inspection rectification plans. The remediation measures are constructed from provincial rectification plans released by the Ministry of Ecology and Environment after the inspection feedback. We code each rectification item in these plans and calculate, for each city, the share of items falling into each timing category. *Short-term remediation share* is the share of city-level rectification items that had been completed, required immediate rectification, or had deadlines within six months when the rectification plan was released. *Completed-at-release share* is the share of city-level rectification items that had already been completed when the rectification plan was released. For each measure, cities are divided into high and low groups based on the median value of the measure. The dependent variable is the log transaction price, $\ln(P_{i,t})$. *Proximity to polluting facility* is the negative distance from a residential community to its nearest monitored facility within the same district, divided by 10 for ease of presentation. Higher values indicate closer proximity. *Inspection* equals one for transactions after the local inspection date. $High$ is an indicator equal to one for cities with values above the median of the corresponding measure. Property attributes and specified fixed effects are included accordingly. The sample period is June 2014 to May 2018. t-statistics based on district-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Short-term Remediation Share		Completed-at-release Share	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Proximity to polluting facility	-0.18***	-0.11**	-0.18***	-0.18
	(-3.30)	(-2.23)	(-3.32)	(-1.49)
Proximity to polluting facility ×	0.06***	-0.02	0.06**	-0.02
Inspection	(2.50)	(-0.45)	(2.64)	(-0.21)
Proximity to polluting facility ×	0.09***		0.10***	
Inspection × *High*	(3.60)		(3.42)	
Property characteristics	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	Yes	Yes	Yes
City× year-month FE	Yes	Yes	Yes	Yes
Number of observations	437,433	71,908	484,808	24,533
Adjusted R^2	0.888	0.849	0.911	0.777

Table 8 National-Monitoring-List-Exit and Repricing of Pollution Exposure

This table reports estimates by the extent of facility removal from the National Key Monitored Enterprises list. *Monitoring-list exit share* is the city-level share of facilities included in the 2015 list that no longer appear in the 2018 list. A higher share indicates greater removal from the national monitoring list and serves as a proxy for realized remediation or regulatory cleanup. Columns (1) and (2) split cities at the median of the exit share. Columns (3) and (4) compare cities in the top and bottom 30% of the exit-share distribution. The dependent variable is the log transaction price, $\ln(P_{i,t})$. *Proximity to polluting facility* is the negative distance from a residential community to its nearest monitored facility within the same district, divided by 10 for ease of presentation. Higher values indicate closer proximity. *Inspection* equals one for transactions after the local inspection date. $High$ is an indicator equal to one for cities with values above the median of the corresponding measure. Property attributes and specified fixed effects are included accordingly. The sample period is June 2014 to May 2018. t-statistics based on district-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Median		30th Percentile	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Proximity to polluting facility	-0.17***	-0.11	-0.17***	-0.11
	(-3.23)	(-1.42)	(-3.23)	(-1.42)
Proximity to polluting facility × *Inspection*	0.06**	0.03	0.06**	0.03
	(2.26)	(0.72)	(2.26)	(0.72)
Proximity to polluting facility × *Inspection* × *High*	0.02**		0.02**	
	(2.21)		(2.41)	
Property characteristics	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	Yes	Yes	Yes
City× year-month FE	Yes	Yes	Yes	Yes
Number of observations	448,455	60,886	448,455	60,886
Adjusted R^2	0.898	0.892	0.898	0.892

Table 9 Realized Changes in Local Environmental Quality

This table reports estimates by realized improvements in local environmental quality. Water quality improvement is measured using changes in city-level water quality classifications reported by municipal Ecology and Environment Bureaus from 2015 to 2018. Air quality improvement is measured using changes in AQI from monitoring-station data over the same period. For each measure, cities are split at the median. The dependent variable is the log transaction price, $\ln(P_{i,t})$. *Proximity to polluting facility* is the negative distance from a residential community to its nearest monitored facility within the same district, divided by 10 for ease of presentation. Higher values indicate closer proximity. *Inspection* equals one for transactions after the local inspection date. $High$ is an indicator equal to one for cities with values above the median of the corresponding measure. Property attributes and specified fixed effects are included accordingly. The sample period is June 2014 to May 2018. t-statistics based on district-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Wastewater		Air Quality	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Proximity to polluting facility	-0.13***	-0.05	-0.32***	-0.18
	(-9.47)	(-1.25)	(-9.47)	(-0.75)
Proximity to polluting facility ×	0.03**	-0.01	0.15**	-0.01
Inspection	(2.85)	(-0.05)	(2.37)	(-0.05)
Proximity to polluting facility ×	0.04**		0.16**	
Inspection × *High*	(2.48)		(2.25)	
Property characteristics	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	Yes	Yes	Yes
City× year-month FE	Yes	Yes	Yes	Yes
Number of observations	72,272	43,804	5,852	53,636
Adjusted R^2	0.827	0.802	0.830	0.812

Table 10 Local Government Environmental Emphasis

This table reports estimates by local government environmental attention. Attention is measured using environment-related keywords in municipal government work reports, including terms related to pollution, governance, inspection, regulation, and enforcement. Keyword intensity is defined as the number of environment-related keywords per 10,000 characters. Columns (1) and (2) split cities by the pre-inspection level of attention, measured using the 2015 government work report. Columns (3) and (4) split cities by the change in attention from the 2015 report to the first post-inspection report. For each measure, cities are split at the median. The dependent variable is the log transaction price, $\ln(P_{i,t})$. *Proximity to polluting facility* is the negative distance from a residential community to its nearest monitored facility within the same district, divided by 10 for ease of presentation. Higher values indicate closer proximity. *Inspection* equals one for transactions after the local inspection date. $High$ is an indicator equal to one for cities with values above the median of the corresponding measure. Property characteristics and specified fixed effects are included accordingly. The sample period is June 2014 to May 2018. t-statistics based on district-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Pre-Inspection Attention		Post-Inspection Change	
	High	Low	High	Low
	(1)	(2)	(3)	(4)
Proximity to polluting facility	-0.18***	0.14	-0.18***	-0.12**
	(-3.45)	(1.31)	(-3.30)	(-2.31)
Proximity to polluting facility ×	0.05**	0.02	0.07**	-0.02
Inspection	(2.24)	(0.52)	(2.52)	(-0.46)
Proximity to polluting facility ×	0.05***		0.09***	
Inspection × *High*	(4.34)		(3.56)	
Property characteristics	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	Yes	Yes	Yes
City× year-month FE	Yes	Yes	Yes	Yes
Number of observations	478,212	31,129	438,201	71,140
Adjusted R^2	0.896	0.849	0.890	0.852

Table 11 Residents' Environmental Concern

This table reports estimates by residents' environmental concern. Concern is measured using two city-level Baidu Search Indices: (i) search volume for *smog* and (ii) search volume for *environmental pollution*. Both indices are scaled by city population. We also use the first principal component of the two population-scaled indices as a third measure. For each measure, cities are divided into high and low groups based on the median value of the measure. Columns (1), (3), and (5) report estimates for high-concern cities, while columns (2), (4), and (6) report estimates for low-concern cities. The dependent variable is the log transaction price, $\ln(P_{i,t})$. *Proximity to polluting facility* is the negative distance from a residential community to its nearest monitored facility within the same district, divided by 10 for ease of presentation. Higher values indicate closer proximity. *Inspection* equals one for transactions after the local inspection date. $High$ is an indicator equal to one for cities with values above the median of the corresponding measure. Property characteristics and specified fixed effects are included accordingly. The sample period is June 2014 to May 2018. t-statistics based on district-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Smog		Environmental Pollution		Principal Component	
	High (1)	Low (2)	High (3)	Low (4)	High (5)	Low (6)
Proximity to polluting facility	-0.19***	-0.12**	-0.17***	-0.05	-0.18***	-0.12**
	(-3.24)	(-2.52)	(-3.38)	(-0.45)	(-3.24)	(-2.50)
Proximity to polluting facility × *Inspection*	0.06**	0.03	0.06**	-0.01	0.06**	0.04
	(2.34)	(0.90)	(2.35)	(-0.12)	(2.32)	(1.02)
Proximity to polluting facility × *Inspection* × *High*	0.02**		0.07***		0.02**	
	(2.51)		(5.24)		(2.23)	
Property characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	Yes	Yes	Yes	Yes	Yes
City× year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	449,496	59,845	459,003	50,338	448,126	61,215
Adjusted R^2	0.891	0.888	0.897	0.869	0.890	0.888

Internet Appendix for "Environmental Enforcement and the Repricing of Pollution Risk"

Appendix IA. Additional Figures and Tables

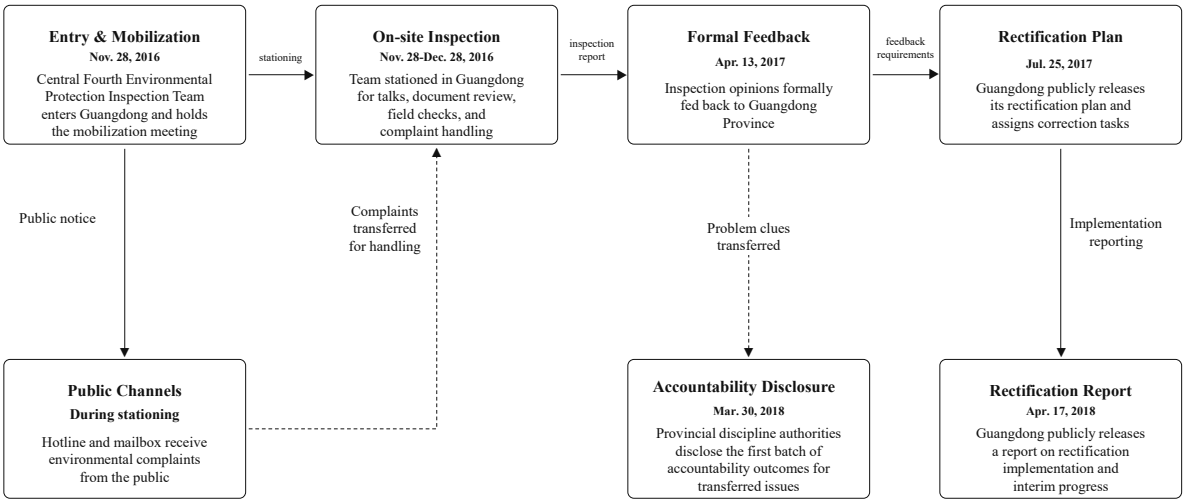
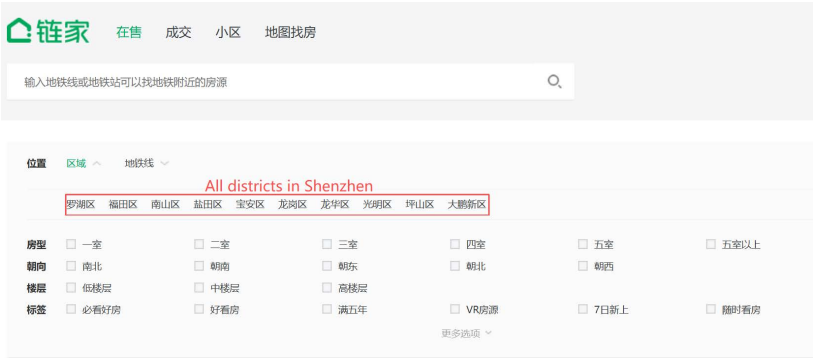


Figure IA1 Central Environmental Protection Inspection Process

This figure summarizes the main steps of the Central Environmental Protection Inspection process, using Guangdong Province as an example. Central inspection teams enter the province, collect public complaints, conduct site visits and investigations, deliver feedback to local governments, and require rectification plans followed by subsequent verification.

Panel A: Platform Coverage



Panel B: Transaction and Listing Records



Panel C: Basic Information of a Property



Figure IA2 Example of Platform Coverage and a Transacted Property

The figure shows an example webpage from Lianjia, a well-established housing transaction platform in China. Panel A displays the coverage of a regional housing market. Panel B illustrates transaction and listing records, while Panel C presents the basic property information available on the platform.

二、废气国家重点监控企业名单（共 3268 家）

Official 2015 National Key Monitored Facilities List: Waste Gas Category (3268 Facilities)

北京市（6 家）

Example Shown: Beijing (6 Facilities)

Administrative Code	City (Prefecture)	County (District)	Facility Code	Facility Name
行政区代码	市（地、州、盟）	县（区）	组织机构代码	企业详细名称
110105	市辖区	朝阳区	72637428X00	神华国华国际电力股份有限公司北京热电分公司
110105	市辖区	朝阳区	X2600055100	华能北京热电有限责任公司
110107	市辖区	石景山区	72260187900	北京京能电力股份有限公司石景山热电厂
110111	市辖区	房山区	10274648700	北京市琉璃河水泥有限公司
110111	市辖区	房山区	10276748001	中国石化集团北京燕山石油化工有限公司
110111	市辖区	房山区	80276350100	中国石油化工股份有限公司北京燕山分公司

Figure IA3 Example of National Key Monitored Polluting Facilities

This figure provides an example of key monitored polluting facilities identified by the Ministry of Environmental Protection in 2015. The full official list covers multiple categories of facilities. The example shown above is from the waste gas (air pollution) category and reports the six facilities listed for Beijing, together with their administrative region codes, district locations, facility codes, and facility names.

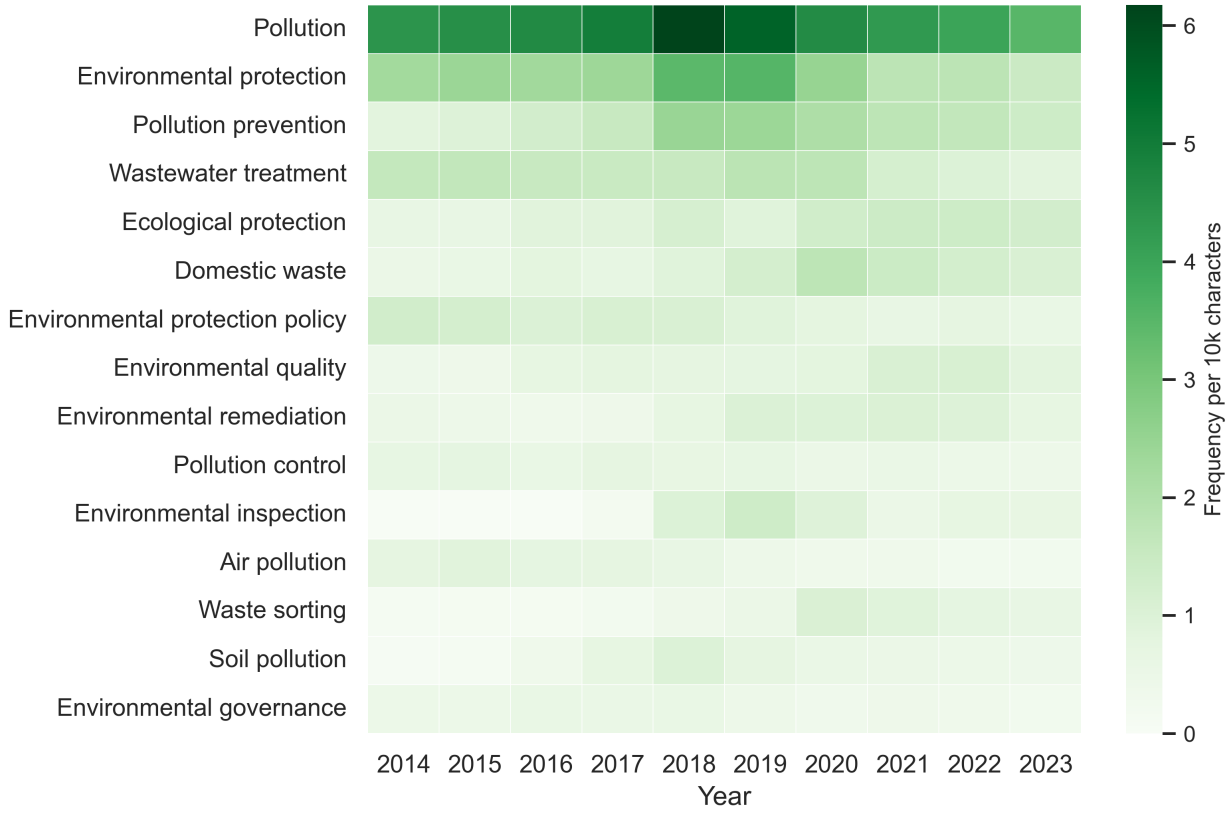


Figure IA4 Heatmap of Keywords in Government Work Report

The figure plots the heatmap of the annual frequency of the top 15 environment-related keywords in municipal government work reports. The strict dictionary contains 87 keywords related to environmental governance, pollution control, environmental inspections, regulation, enforcement, monitoring, and discharge permits. Each cell is calculated as the total count of a given keyword across city reports in a year divided by the total number of Chinese, English, and numeric characters in those reports, multiplied by 10,000.

Table IA1 Alternative Proximity Measures and Fixed Effects for Unit Prices

This table reports coefficient estimates from additional specifications using the log unit price as the dependent variable. Columns (1) and (2) estimate the specification with alternative fixed effects. Columns (3)-(5) use the negative logarithm of distance to the nearest polluting facility as the proximity measure, divided by 10 for ease of presentation. Controls and fixed effects are included as indicated. The sample covers the period from June 2014 to May 2018 for the first-round inspection. t-statistics based on city-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Alternative Fixed Effects		Log of Proximity		
	(1)	(2)	(3)	(4)	(5)
Proximity to polluting facility	-0.18***		-0.46***	-0.44***	
	(-10.62)		(-6.76)	(-7.04)	
Proximity to polluting facility ×	0.07***	0.04***	0.23***	0.17***	0.16***
Inspection	(6.84)	(7.29)	(5.61)	(5.06)	(6.18)
Discount	-0.11***		-0.23***	-0.27***	
	(-5.89)		(-4.91)	(-4.68)	
Property characteristics	Yes	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	No	Yes	Yes	No
Community FE	No	Yes	No	No	Yes
City×year-month FE	No	Yes	Yes	No	Yes
District×year-month FE	Yes	No	No	Yes	No
Number of observations	533,431	528,425	533,583	533,431	528,425
Adjusted R^2	0.896	0.968	0.892	0.895	0.968

Table IA2 Alternative Proximity Measures and Fixed Effects for Listing Prices

This table reports coefficient estimates from additional specifications using the log listing price as the dependent variable. Columns (1) and (2) estimate the specification with alternative fixed effects. Columns (3)-(5) use the negative logarithm of distance to the nearest polluting facility as the proximity measure, divided by 10 for ease of presentation. Controls and fixed effects are included as indicated. The sample covers the period from June 2014 to May 2018 for the first-round inspection. t-statistics based on city-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Alternative Fixed Effects		Log of Proximity		
	(1)	(2)	(3)	(4)	(5)
Proximity to polluting facility	-0.16***		-0.44***	-0.41***	
	(-6.69)		(-4.90)	(-4.56)	
Proximity to polluting facility ×	0.05***	0.03***	0.18***	0.11***	0.13***
Inspection	(4.87)	(12.37)	(6.79)	(3.24)	(9.14)
Discount	-0.12***		-0.26***	-0.30***	
	(-4.80)		(-3.51)	(-4.01)	
Property characteristics	Yes	Yes	Yes	Yes	Yes
Nearest polluting facility FE	Yes	No	Yes	Yes	No
Community FE	No	Yes	No	No	Yes
City×year-month FE	No	Yes	Yes	No	Yes
District×year-month FE	Yes	No	No	Yes	No
Number of observations	401,475	396,455	401,614	401,475	396,455
Adjusted R^2	0.916	0.970	0.913	0.915	0.970

Table IA3 Baseline Estimates for Communities 10–15 km from the Nearest Facility

This table replicates the baseline specifications for communities whose nearest monitored facility is located between 10 and 15 kilometers away. The dependent variable is the log transaction price, $\ln(P_{i,t})$. *Proximity to polluting facility* is the negative distance from a community to its nearest polluting facility within the same district, divided by 10 for ease of presentation; thus, higher values indicate closer proximity to a polluting facility. *Inspection* equals one for transactions after the relevant inspection date. Column (1) reports the two-way fixed effects (TWFE) estimate, while column (2) reports the stacked DID estimate. In the stacked DID specification, each treated group is matched to a corresponding control group and the nearest-polluting-facility and city-by-year-month fixed effects are interacted with stack indicators; because the same observations may enter multiple matched treatment-control stacks, the number of observations in column (2) is larger than in column (1). Controls and fixed effects are included as indicated. t-statistics based on city-clustered standard errors are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	TWFE	Stacked DID
	(1)	(2)
Proximity to polluting facility	-0.78	-0.45
	(-1.40)	(-1.77)
Proximity to polluting facility ×	0.25	0.13
Inspection	(1.39)	(1.95)
Discount	-0.53	-0.32
	(-1.91)	(-1.56)
Property characteristics	Yes	Yes
Nearest polluting facility FE	Yes	Yes
City×year-month FE	Yes	Yes
Number of observations	33,259	53,425
Adjusted R^2	0.873	0.891

Table IA4 Provincial Feedback Measures from the First Round of CEPI

This table reports province-level inspection feedback and enforcement measures from the first round of the Central Environmental Protection Inspection. *Public Complaints* is the number of environmental complaints received and accepted by the inspection team. *Penalty Cases* is the number of cases filed for administrative penalty. *Officials Held Accountable* is the number of local officials held accountable for environmental governance failures. All measures are cumulative counts as of the date on which the central government released the provincial feedback report.

Batch	Province	Feedback Release Date	Public Complaints	Penalty Cases	Officials Held Accountable
Pilot	Hebei	Apr. 2016	2,856	125	366
Batch 1	Jiangsu	Nov. 2016	2,451	1,384	449
Batch 2	Shanghai	Feb. 2017	1,893	926	56
Batch 2	Beijing	Feb. 2017	2,346	188	45
Batch 2	Guangdong	Feb. 2017	4,350	3,346	684
Batch 2	Chongqing	Feb. 2017	1,824	467	40
Batch 2	Hubei	Feb. 2017	1,925	359	522
Batch 3	Liaoning	Jun. 2017	6,991	1,706	850
Batch 3	Tianjin	Jun. 2017	4,226	1,654	139
Batch 3	Fujian	Jun. 2017	4,903	1,763	444
Batch 3	Anhui	Jun. 2017	3,719	803	476
Batch 3	Hunan	Jun. 2017	4,583	1,203	1,359
Batch 4	Shandong	Oct. 2017	8,170	1,471	1,268
Batch 4	Zhejiang	Oct. 2017	6,920	4,387	350
Batch 4	Sichuan	Oct. 2017	8,966	2,268	1,293