The Value of Environmental Monitoring

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Abstract

Governments allocate substantial resources to regulate the environmental consequences of industrial activity. However, little is known about the economic value associated with such oversight. We document a 1.1% increase in US housing values following the establishment of a nearby monitoring station. This positive price effect is attributable to improvements in air quality as we demonstrate a 46.7% reduction in toxic emissions and a 2.6% decrease in the number of industrial facilities in the area subject to additional monitoring. Conservative estimates suggest that the value of new monitoring stations exceeds $52 billion.

Keywords: Regulatory Compliance, Environmental Monitoring, Property Values

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1. Introduction

Governments allocate substantial resources to oversee and regulate environmental consequences of firms' operations. In response, firms incur significant expenditures to comply with these regulations and may strategically respond to circumvent this regulatory oversight. Beyond the environmental impact of such oversight, policy makers require knowing the net costs and benefits of potential regulations to make informed decisions. This paper provides such assessment by investigating the value and effectiveness of air quality monitoring stations, one of the most widely employed environment monitoring tools. Specifically, we investigate the effects of monitoring station establishment on property prices, facility-level emissions, and air quality.

This research question is important for two reasons. First, prior investigations into the effectiveness of air quality monitoring stations yield mixed findings. For example, Mu, Rubin and Zou (2022), reveal that local governments may cease monitoring operations in anticipation of declining air quality. Similarly, Zou (2021) documents an increase in pollution levels during periods of monitoring station inactivity, while Grainger and Schreiber (2019) highlight that the placement of monitors tends to avoid areas with high pollution concentrations. These studies raise questions about the effectiveness of air quality monitoring stations, suggesting potential principal-agent incentive misalignments in local agencies' pollution monitoring activities. In contrast, a more recent study of monitoring station deployment in China by Axbard and Deng (2024) finds that such monitoring efforts can lead to intensified enforcement inspections by local governments, subsequently contributing to enhanced air quality. However, it is crucial to recognize the unique contextual factors in the Chinese setting, where the monitoring station deployments are part of a broader environmental policy that ties environmental performance to promotion incentives for local officials.[1,2] Thus, it is not yet clearly understood whether and how a monitoring station, on its own, impacts aggregate environmental outcomes.

Second, our paper is the first study that brings insights into the potential value that monitoring stations may provide to local communities, extending beyond mere regulatory compliance to tangible benefits related to enhanced property values. Many countries lack access to air monitoring stations—illustrated by an estimate suggesting that 60% of countries or 1.3 billion people lack any PM2.5 monitoring (Martin et al., 2019)—due to the high cost associated with installing and operating monitors. By showing effects on the housing market, we provide systematic evidence on the cost-benefit tradeoff associated with monitoring stations, which is valuable for future policymaking regarding the deployment of such monitoring tools.

To analyze the impact of monitoring stations on real estate values, we combine the real estate transaction-level dataset from Corelogic with data on monitoring stations obtained from the Environmental Protection Agency's (EPA) Air Quality System (AQS) to determine the distance of a transacted property and, consequently, its exposure to the establishment of a monitoring station. In our baseline analyses, we categorize properties within 5 kilometers of a monitoring station as potentially affected by the station's establishment. To mitigate confounding factors arising from variations in locality characteristics and time-varying shocks in the property market, we restrict our main analysis to transactions of properties within 10 kilometers of a monitoring station, spanning 3 years before and after the station's establishment. Our baseline sample thus comprises over 3.8 million sales of residential properties between 1995 to 2020,

[1] In 2014, Premier Li Keqiang declared a "war against pollution" at the opening of China's annual meeting of the National People's Congress. This announcement came several months after the Chinese government introduced the National Air Quality Action Plan (2013), which outlined specific targets to improve air quality by the end of 2017. See, https://aqli.epic.uchicago.edu/policy-impacts/china-national-air-quality-action-plan-2014/, for more information.

[2] A few other studies also investigate the same pollution control policy in China. For example, Barwick et al. (2023) document that increased access to pollution information leads to avoidance behaviour, which, in turn, reduces health harms from pollution. Greenstone et al. (2022) find that the monitoring automation limits the manipulation of pollution data by local governors.

examining the effects of 721 particulate matter monitoring stations that opened between 1992 to 2020.

Our baseline analysis shows that the establishment of monitoring stations contributes to enhanced property values in the surrounding area. Specifically, using a difference-in-differences identification strategy, we observe a 1.1% increase in the value of houses located within 5 kilometers of a monitoring station after the station's establishment, compared to those located within 5 to 10 kilometers of the same monitoring station. Further insights from quantile regression estimates indicate that most of the price increase is concentrated among low-priced houses, particularly those in the first four price deciles, with houses in the 1st and 2nd deciles experiencing the largest price appreciation of 4.6% and 3.8% respectively.

One empirical challenge in identifying the price effect of monitoring station establishments on housing prices is the strategic selection of monitoring sites. Specifically, Grainger and Schreiber (2019) provide evidence that regulators tend to avoid pollution hotspots, and such avoidance behavior is less prominent in high-income and predominantly white areas. To address this identification issue, our primary method involves comparing properties within the same locality but at varying distances from the monitoring stations. In our baseline specification, houses are categorized as *treated* if they are situated within 5 kilometers of the monitoring station, and as *control* if they are situated within 5 to 10 kilometers of the monitoring station. We include *monitoring station* × *transaction year-month* fixed effects and compare *treated* houses to *control* houses that are sold in the same month and located in the vicinity of the same monitoring station. This approach safeguards our baseline estimates from internal validity issues arising from differences in locality characteristics due to endogenous site selection. Thus, to the extent that monitoring stations are more likely to be placed in less polluted and higher-income areas, our baseline estimate of 1.1% is likely an underestimate of the true price effects, drawing from our findings that indicate larger price effects in lower-priced houses and more polluted areas.

To further control for observable differences in properties, we interact station fixed effects with additional transaction- and property-level attributes. In the most stringent specification, our findings remain robust when comparing *treated* houses to *control* houses with identical property characteristics (e.g., number of bedrooms, number of bathrooms, residential property type, property age group, building square footage, land square footage, pool indicator), transaction characteristics (e.g., cash purchase, sale type, purchase motive, buyer type), sold in the same month and within 10 kilometers of the same monitoring station. The results also remain consistent across a battery of robustness tests, including the use of alternative sampling windows, distance from monitoring stations (10 to 20 kilometers), alternative identification specification, and the use of a subsample that excludes counties affected by environmental policy shocks, specifically the *nonattainment* designations under the Clean Air Act.

We conduct a back-of-the-envelope calculation to illustrate the value generated by the establishment of monitoring stations, using the baseline price effect of 1.1% and the pre-establishment average transaction price of treated houses, which is $271,011 in 2020 dollars. Based on a conservative estimate of over 17.5 million housing units situated within 5 kilometers of any particulate matter monitoring station, we show that the establishment of monitoring stations results in a total increase of over $52 billion (=17,500,000×$271,011×1.1%) in housing values. Thus, our estimates indicate that monitoring stations create monetary value that benefits the local community, in addition to the potential health and labor benefits associated with reduction in air pollution (see for example Brunekreef and Holgate, 2002; Chay and Greenstone, 2005; Hanna and Oliva, 2015; Aragón , Miranda and Oliva, 2017; He, Liu and Salvo, 2019; Borgschulte, Molitor and Zou, 2022).

Next, we investigate two potential mechanisms that could drive the positive price effects. The first mechanism, denoted as the *Improved Air Quality Channel*, suggests that monitoring stations function as compliance enforcement tools that deter firms from engaging in environmental evasion behavior, thereby reducing firms' emissions, improving air quality and contributing to higher house prices. To explore this mechanism, we examine changes in pollution levels following the establishment of a monitoring station. We consider two measures of pollution—facility-level annual toxic emissions and grid-level satellite measure of daily aerosol concentration. In line with the *Improved Air Quality Channel*, our findings indicate that facilities reduce toxic emissions by 46.7% after the establishment of a nearby monitoring station. Notably, most of this reduction stems from a significant decrease in air emissions, while responses in water and land emissions are muted. On the extensive margin, the number of TRI facilities drops by 2.6% following the station's establishment. As a supplementary analysis to the facility-level findings, using a satellite measure of aerosol concentration, we observe a 3.1% reduction in pollutant concentration following the establishment of a monitoring station. These results align with previous study that demonstrates monitoring stations improve air quality by enhancing environmental regulatory actions (Axbard and Deng, 2024).

The second mechanism, denoted as the *Information Channel*, implies that new information about air quality in the locality, previously unavailable but now accessible following the establishment of a monitoring station, corrects incomplete information in the market. This, in turn, influences housing transaction prices as individuals incorporate updated air quality information into housing prices. To test the *Information Channel* mechanism, we identify areas where *actual* air quality differs from *perceived* belief. The underlying assumption is that if the *Information Channel* is the primary mechanism, then the establishment of a monitoring station should lead to updated beliefs about air quality, resulting in potential changes in property prices in areas with disparities between *perceived* and *actual* air pollution levels but no price changes in areas where *perceived* belief aligns with *actual* air quality. Using the number of industrial facilities surrounding the monitoring station as a proxy for *perceived* pollution levels and average PM 2.5 values in the first year since the station's establishment as a proxy for *actual* pollution levels, we categorize areas into four groups: areas with *perceived* low pollution and *actual* low pollution (LL) levels, areas with *perceived* high pollution and *actual* high pollution (HH) levels, areas with *perceived* low pollution and *actual* high pollution (LH) levels, and areas with *perceived* high pollution and *actual* low pollution (HL) levels. Our findings reveal a statistically significant positive price effect in HH areas, which contradicts the *Information Channel* that posits no effect in areas where the *perceived* levels of air pollution match the *actual* level. In addition, we directly test the *Information Channel* using a sample of properties near non-regulatory monitoring stations that provide values for reporting daily Air Quality Index values rather than for regulatory purposes. Our analysis reveals no statistically significant price effects upon the station's opening. These findings rule out the *Information Channel* being the primary mechanism underlying the estimated price effect resulting from the establishment of monitoring stations.

To the best of our knowledge, our paper provides the first empirical estimate of the values of air quality monitoring stations, considering the effects on housing values in addition to effects on air pollution. Specifically, we document the causal mechanism through which monitoring stations influence property prices by discouraging firm-level emissions and, consequently, improving air quality. Our findings thus complement existing studies on environmental quality and willingness-to-pay. For example, using the opening of industrial plants as a negative shock to local air quality, Currie et al. (2015) find an 11% decline in the values of houses nearby. Similarly, Chay and Greenstone (2005) exploit county-level tightening of environmental regulation following the designation of nonattainment status by the EPA and identify a causal negative relation between pollutant concentration and housing values. In a similar vein, our study leverages the establishment of monitoring stations as a shock to air quality, and we document the positive price effect of monitoring station establishment, driven by improved air quality.[3] Our study also contributes to the environmental justice literature that documents a correlation between pollution and poverty. Specifically, the estimates from quantile treatment regressions suggest that lower-priced houses experience a larger increase in value from the establishment of a monitoring station. These findings point towards the monitoring stations serving as a valuable instrument in addressing long-standing environmental inequality in the country.

Our paper also contributes to the literature concerning the impacts of environmental monitoring and corporate environmental decisions by documenting that the establishment of monitoring stations leads to a reduction in facility-level emissions on the intensive margin, as well as a decrease in the number of industrial facilities on the extensive margin. Our findings underscore the importance of regulatory risks for firms, which increase with the presence of monitoring, aligning with existing evidence suggesting that investor monitoring improves firm environmental performance (Shive and Forster, 2020; Tao, Hui and Chen, 2020; Azar et al., 2021; Khan, Matsusaka and Shu, 2023; Ren et al., 2023).

Finally, our work is closely related to studies examining the impacts of environmental regulations on emissions outcomes. Previous research has documented evasive behavior among profit-maximizing firms (e.g., Mu, Rubin and Zou, 2021; Zou, 2021; Alexander and Schwandt, 2022; Agarwal et al., 2023). Among all, for instance, Bartram, Hou and Kim (2022) examine the impact of California cap-and-trade program and find that financially constrained firms reallocate emissions and output away from the policy-hit region to avoid regulatory costs. Similarly, Gibson (2019) reveals that firms regulated by air quality regulations substitute air

[3] These results also align with Axbard and Deng (2024) and the literature on environment and health. See, for example, Chay and Greenstone (2003), Currie, Neidell and Schmieder (2009), Currie, Greenstone, and Moretti (2011), and Currie and Walker (2011).

emissions with water emissions. Our paper demonstrates that air quality monitoring stations serve as effective regulatory tools that can influence firms' emission behavior, consistent with existing studies that show environmental regulations reduce industrial production and economic activity (Becker and Henderson, 2000; Greenstone, 2002; Greenstone et al., 2012), and consequently, emissions (Brown, Martinsson and Thomann, 2022; Chen, et al., 2022; Dasgupta, Huynh and Xia, 2023).

The remainder of the paper is organized as follows. Section 2 provides background and a description of the data sources and outlines our main data sample. Section 3 presents our identification strategy and baseline results, along with the results of robustness tests and heterogeneity analyses. Section 4 delves into two potential mechanisms driving the baseline results, and Section 5 concludes.

2. Background and Data

2.1 Clean Air Act and Air Quality Monitoring

First established in 1963, the Clean Air Act (CAA) serves as the foundational framework for environmental regulation in the United States. A crucial component of the CAA is the imposition of National Ambient Air Quality Standards (NAAQS) by the US Environmental Protection Agency (EPA), which specify permissible concentrations of air pollutants to safeguard public health and the environment.

The CAA mandates that state governments monitor air quality within their respective jurisdictions. The deployment of monitoring stations is overseen by local regulatory agencies (at the state, county, or tribal level), with guidelines suggesting the placement of monitors in zones of high pollution concentration, densely populated areas, and consideration of meteorological factors like wind direction (US EPA, 2008). These guidelines are advisory, and the local agencies can exercise discretion in choosing monitor locations.[4]

The EPA monitors compliance with the NAAQS using air quality data collected by a network of sensors and designates counties adhering to the standards as attainment counties, while those violating the standards as non-attainment counties, which are subject to heightened regulatory oversight and costs. States are required to formulate a State Implementation Plan (SIP), outlining specific plans for implementation, maintenance, and enforcement of the NAAQS. Non-attainment states must include detailed plans and additional requirements to mitigate air pollution in those non-attainment areas. Initiatives may involve the adoption of pollution abatement technologies in existing firms, the restriction of new constructions or modifications of major sources for pollution, or the physical or operational reduction of production capacity.

2.2 Main Sample

We collect from CoreLogic the transaction records encompassing residential properties sold nationwide during the period from 1995 to 2020.[5] The data contain information on the transaction price, detailed geographic information, property type (e.g., single family residence, condominium, apartment, duplex), number of bedrooms and bathrooms, property and land square footage, and effective year of construction. The data also contain transaction-level details including information regarding whether the transaction constituted a resale, whether it was an all-cash deal, whether the purchaser was a corporation, and whether the purchase was intended for investment purpose.

[4] See, for example, Grainger and Schreiber (2019) that examine the characteristics of monitor locations.

[5] CoreLogic is a national real estate data provider that collects real estate data from tax assessors and recorders officers across the nation.

The precise geo-coded location data of each property enables us to determine the property's distance to the particulate matter monitoring stations. The locations and additional information about these monitoring stations are extracted from the daily summary data of fine particulate matter (PM2.5) in the Air Quality System (AQS). Our focus is on monitoring stations with PM monitors used for regulatory compliance with PM2.5 standards. We exclude monitors not intended for regulatory purposes. To implement our research design, we focus on monitoring stations equipped with PM monitors operating at the neighborhood spatial measurement scale, covering air quality measurements within the surrounding areas spanning from 0.5 kilometers to 4 kilometers from the pollutant source.[6, 7]

Figure 1 illustrates the geographical distribution of PM monitoring stations overlaid on the spatial distribution of the satellite measure of pollution exposure in 2000.[8]Areas in the north and south, as well as the coastal west, have a higher concentration of monitoring stations. Not surprising, these areas experience higher levels of aerosol concentration, suggesting that the placement of monitoring station networks is endogenous. In Figure 2, we show the total number of monitoring stations categorized by year of construction. There are more than 1,300 monitoring stations installed with PM monitors, and a significant percentage were constructed after 1997, the year when the Environmental Protection Agency (EPA) first established the PM2.5 standards.[9]

We filter the CoreLogic data in several steps. First, we focus solely on arms-length transactions involving residential properties, including single-family houses, condominiums,

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[6] Air monitoring networks have various spatial scales, including 1 meter to 100 meters (microscale), 100 meters to 500 meters (middle scale), 4 kilometers to 50 kilometers (urban scale), and 10 kilometers to 100 kilometers (regional scale). Neighborhood scale monitors, covering 0.5 kilometers to 4 kilometers, are the most prevalent, constituting over 70% of the monitoring network in the country.

[7] Our empirical results remain robust when studying universal monitoring network in the country, irrespective of the type of pollutants the monitors measure, their measurement scale, or whether they are intended for regulatory purposes.

[8] Pollution exposure is calculated by averaging the daily aerosol optimal depth across the year 2000.

[9] See, https://www.epa.gov/pm-pollution/timeline-particulate-matter-pm-national-ambient-air-quality-standards-naaqs, for more information.

duplexes and apartments. This excludes properties transacted among family members, short sales and foreclosure sales. Second, we remove outliers by excluding transactions occurring at extreme prices—below the 1st or above the 99th percentile of the distribution of raw transaction prices. Additionally, we exclude observations reporting implausible property characteristics, such as having no bedrooms, and by eliminating observations with values below 0.1st percentile or above the 99.9th percentile of the distribution of the number of bedrooms, bathrooms, building square footage, land square footage and property age as of transaction. We only include observations with non-missing property attributes. Finally, to minimize potential confounders arising from locational heterogeneities, we confine our baseline sample to transactions of properties located within 10 kilometers of a monitoring station. The resulting dataset has 3,822,505 transactions.

Panel A of Table 1 presents summary statistics for the transactions in our baseline sample. The average house, across all transactions in all years, features 1,711 square feet of living area on a 18,429 square foot lot; it is 34 years old with 3 bedrooms and 2 bathrooms, located 5.75 kilometers from a monitoring station, and is sold at a price of $221,890.

Panel B provides summary statistics for transactions grouped into two categories based on their distances to monitoring stations: within 5 kilometers of a monitoring station or within 5 kilometers to 10 kilometers of a monitoring station. In general, houses located in these two categories are similar. They have nearly identical transaction-level attributes (i.e., resale, cash purchase, corporate buyer, owner occupied), but houses located closer to monitoring stations are smaller, potentially leading to a lower transaction price. Nevertheless, we control for any observable differences in both property-level and transaction-level characteristics between the two groups throughout our empirical analysis.

2.3 Supplemental Data

We collect facility-level emissions data from the Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) database, covering the years 1995 to 2020. TRI collects information on the discharge of hazardous chemicals at the facility level, providing details on the total amount of chemicals released into the air, water, and land, both on-site and off-site.[10] Additionally, it also includes information about the facility's geocoded location, allowing us to calculate its distance to the monitoring station, and consequently, its exposure to the monitoring station's establishment. For each facility in a year, we aggregate the emission data by summing the releases of all toxic chemicals reported by the facility in that specific year.

We obtain a measure for atmospheric particle pollution using satellite data from National Aeronautics and Space Administration's (NASA) Moderate Resolution Imaging Spectroradiometer (MODIS) algorithm. This algorithm retrieves aerosol concentrations by measuring the vertical extinction of the solar beam caused by dust and haze, leveraging information on the aerosol's light-scattering and absorption characteristics at different spectral wavelengths. Termed aerosol optical depth (AOD), this measure is a dimensionless index with a theoretical range of -0.05 to 5, where higher values indicate higher level of aerosol concentration.[11] It is assessed at a spatial resolution of 10 kilometers × 10 kilometers and serves as an estimate of ground-level pollution concentrations.[12] These estimates demonstrate robust performance, closely aligning with the *ground truth* measured by EPA monitors (Liu et al.,

[10] Industrial facilities are mandated to submit annual reports to the TRI if they meet the following criteria: (1) employ a minimum of 10 full-time workers, (2) operate within one of approximately 400 industries classified based on the six-digit NAICS code, and (3) use one of roughly 780 chemicals in quantities surpassing the EPA-established threshold.

[11] According to the specifications outlined in https://modis-images.gsfc.nasa.gov/MOD04_L2/format.html, we substitute negative AODs with zeros. This adjustment is made because MODIS lacks sensitivity over land to retrieve aerosol levels better than +/-0.05. Consequently, in extremely clean conditions, the algorithm cannot determine whether the AOD is 0, 0.05 or -0.05.

[12] We follow the data cleaning procedures outlined in Zou (2021). To create grid-level dataset, we re-grid daily aerosol raster files to a resolution of 1km × 1km. We then overlay these re-gridded rasters onto a fixed 10km × 10km gridded map obtained from the US National Information Center. The daily aerosol level for each 10km × 10km is the average aerosol concentration across all 1km × 1km grids falling within the grid on a given day.

2007; Lee et al., 2012). From 2000 to 2020, the average aerosol concentration in the United Sates is 0.15, with the 25^{th} and 75^{th} percentile being 0.03 and 0.15, respectively.

We collect daily meteorological data from 2000 to 2020 from Daymet, which provides gridded estimates of daily weather parameters, including maximum temperature, minimum temperature, and precipitation, at a 1 kilometer × 1 kilometer spatial resolution. We map this meteorological data with the grid-level data of aerosol concentrations. For each grid in the aerosol data, the weather estimate is calculated as the average across all 1 kilometer × 1 kilometer grids falling within the larger grid on a given day.

3. Effect of Monitoring Station's Opening on Real Estate Prices

3.1 Identification

To the extent that the presence of monitoring stations enforces environmental regulations by deterring firms from emitting unauthorized pollutants and thus leading to improved air quality, properties situated in close proximity to the monitoring station should command higher prices compared to properties located further away. Our empirical design estimates the impact of monitoring station establishment by comparing the property price changes before and after their establishment. Specifically, we compare properties that transact in the same year-month and locality, and are comparable in terms of property and transaction characteristics but differ in their distance from the monitoring station. For our baseline analysis, we estimate the following regression:

$$Ln(Price)_{it} = \beta After_t \times \mathbb{1}[\text{Distance}_\text{i} < 5\text{km}] + X_{it}\phi + \lambda_z + \theta_{mt} + \varepsilon_{it} \qquad (1)$$

where the dependent variable $Ln(Price)_{it}$ is the natural logarithm of property i's transaction price in year-month t. X_{it} is a vector of property- and transaction-level controls, which include indicators for number of bedrooms, number of bathrooms, property type, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, cash purchase, sale type (resale or developer sale), corporate buyer, and the motive for purchase (investment or owner occupation).[13] Considering that monitoring stations are generally strategically positioned in areas with high pollution concentrations and dense populations, we include 100 distance indicators for properties to the monitoring station (with each bin covering a 0.1-kilometer range) to account for heterogeneities based on distance to monitoring station. In addition, we include zip code fixed effects, λ_z, to control for all time-invariant determinants of property prices within zip codes, and monitoring station × year-month fixed effects, θ_{mt}, to flexibly capture trends in property values within the 10-kilometer radius locality over time. The baseline sample is restricted to transactions of properties within a 10-kilometer radius of monitoring stations, spanning a period of 6 years, encompassing 3 years before and 3 years after the establishment of the monitor sites. Standard errors are clustered at the zip code level.[14]

Our explanatory variable of interest is the interaction between two indicators: $After_t$, which equals 1 if the transaction occurs after the monitoring station's establishment, and $\mathbb{1}[\text{Distance}_i < 5\text{km}]$, which equals 1 if the property is situated within 5 kilometers of the monitoring station. The parameter, β, thus captures the effects of the establishment of monitoring stations on house prices. If the presence of monitoring stations discourages

[13] Since certain counties do not report information about the number of bedrooms and/or bathrooms but otherwise provide good coverage, in an unreported regression, we replicate the baseline specification but include the observations with missing bedrooms/bathrooms by introducing separate fixed effects. Results are identical to the baseline findings.

[14] Unreported regression results show that the statistical significance of the estimates remains consistent when standard errors are clustered at the monitoring station level, county level, or census tract level.

environmental non-compliance among firms, we should expect a positive β, as the resulting improved environmental outcomes are likely to be capitalized into house prices.

3.2 Baseline Results

Table 2 presents baseline regression results on the house price effect of the monitoring station's establishment. We find a significant positive effect of station's establishment on house prices in Column 1. The coefficient of 0.011 suggests that house prices increase by 1.1% after the opening of the monitoring station, compared to similar houses sold at the same time but located further away from the same monitoring station.

Figure 3 depicts the dynamic price effects using the same regression specification as in Column 1. Additional indicators for the number of periods before and after the monitoring station's establishment are included, with the reference period omitted in the dynamic regression being the 12th quarter before the establishment. A significance test between the coefficients of the pre-establishment periods indicate that they are not significantly different from zero. This suggests that the price effect during the pre-establishment period is both economically and statistically muted, consistent with the parallel-trend assumptions.[15]

Focusing on the post-establishment periods, we observe that the prices of properties near the monitoring station increase by approximately 1.1% in the first year after its opening. The positive price effect further rises to 1.4% in the second year and remains at the similar level in the third year. These results imply that the monitoring station has a lasting impact, creating long-term value that is reflected in house prices.

To alleviate concerns about potential differences between transactions of properties based on differences in distance to the monitoring stations, in Columns 2 to 4, we incrementally

[15] In Appendix Figure 1, we present the dynamic price effects using the number of years to opening (instead of quarters) as the time indicators. Panel A shows the dynamic effects over 3-year, while Panel B shows the effects over an extended 5-year post-establishment period. In both figures, we observe a consistent parallel pre-trend.

introduce interactions between the monitoring station × time fixed effects with fixed effects for property type (Column 2), sale type (Column 3), and an indicator for owner-occupation (Column 4). In each case, we continue to find a significantly positive effect of monitoring station's opening on house prices. In Column 5, we further interact the fixed effects with all property-level and transaction-level attributes. Although the sample size reduces significantly due to the large number of singleton observations resulting from the extensive fixed effects, we still find statistically significant positive price effect. Specifically, prices of properties located within 5 kilometers of the monitoring station increase by 3.9% after its establishment, compared to properties transacted in the same month, with the same property type, sale type, property size, number of bedrooms and bathrooms, and purchased by buyers with the same profile and purchase motives but located further away from the monitoring station.

We also explore various fixed effects specifications. In addition to the baseline specification that compares properties close to the monitoring station to properties located within the 5- to 10-kilometer radius of the same monitoring station, we also compare to properties situated within the 5- to 10-kilometer radius of all monitoring stations within the same zip code (Columns 6 and 7), as well as the same county (Columns 8 and 9). Our results remain consistent across these different specifications.

3.3 Robustness Tests

Alternative Identification Specification

Recent development in the econometrics literature suggest that estimates obtained from generalized difference-in-differences are likely biased when there is staggered treatment timing and treatment effect heterogeneity (de Chaisemartin and D'Haultfœuille, 2020; Callaway and Sant'Anna, 2021; Goodman-Bacon, 2021; Baker, Larcker and Want, 2022). Our baseline results are less susceptible to these biases (i.e., the use of earlier-treated units as controls for later-treated units) because our baseline specification includes monitoring station × time fixed effects, which compare *treated* houses to *control* houses located within the vicinity of the same monitoring station and transacted in the same period.

Nevertheless, we explore alternative specifications to ensure the robustness of the estimates for price effects. One such alternative is *stacked regression* analysis (Cengiz et al., 2019; Deshpande and Li, 2019; Baker, Larcker and Want, 2022). In this method, each establishment of a monitoring station is a distinct treatment event with monitoring station indicators serving as the event-specific identifiers. We replace the distance-bin fixed effects with the interaction of distance-bin fixed effects and monitoring station fixed effects. This inclusion complements the original monitoring station × time fixed effects of the baseline specification. Results are presented in Table 3, and the estimates for price effects remain consistent with the baseline across all specifications.

Alternative Comparison Group, Sampling Periods and Sample Construction

The price effects of a monitoring station's establishment may spill over to properties in the baseline comparison group. Given that air pollutants can travel over long distances , any reduction in emissions by firms around the monitoring stations collectively contributes to the improved air quality in the surrounding areas. If this occurs, our baseline estimate will underestimate the true price effect.

To test this spillover effect, we replace the baseline comparison group with properties situated within 10 to 20 kilometers of the monitoring station, and the results are reported in Table 4 Panel A. In line with our conjecture, we observe a larger price premium ranging from 1.3% to 2.8% for properties near (x to y km) the monitoring station after its opening.

We also examine the distance decay of price effects by implementing various distance buffers around the monitoring station. In Appendix Figure 2, we plot the coefficients of price effects as a function of properties' distance to the monitoring stations. In particular, we categorize properties into 10 distance bins, ranging from 0-1 kilometer to 9-10 kilometers, each with a 1-kilometer buffer. We estimate the price effects of monitoring station establishment separately for properties in each bin, using properties situated within 10 to 20 kilometers of the monitoring station as the comparison group. Our findings reveal significant positive price effects up to the 4-5-kilometer bin, with houses closest to the monitoring station experiencing the highest value increase of more than 2%. Beyond 5 kilometers, the price effect becomes statistically insignificant and diminishes in magnitude, suggesting that the effectiveness of monitoring stations as environmental conveyance tools is highly localized.[16]

Our results also remain robust across different sampling periods. Panel B and C present estimates for the price effects using the same specification as in Table 2 but with varying post-establishment periods, including a longer five-year period and a shorter one-year period respectively. Unreported regressions demonstrate consistent results even when we extend the pre-establishment period from the baseline of three years to five years.

One possible explanation of the positive price effects is that the area where the monitoring station is located may be subject to an environmental regulatory shock. The Clean Air Acts establish pollutant-specific National Ambient Air Quality Standards (NAAQS), which specify the maximum allowable concentrations of certain criterion air pollutants. Annually, the EPA identifies counties that are in violation of these NAAQS, designating them as *nonattainment* based on air pollution monitor measurements within these counties or nearby areas. If monitoring stations are more likely to be placed in *nonattainment* areas, this regulatory shock could potentially lead to an overestimation of the estimated price effects, considering the positive relationship between nonattainment status and housing prices (Chay and Greenstone, 2005; Grainger, 2012).

[16] The distance decay relationship, where price effects diminish with distance to monitoring stations, remains consistent when using the baseline comparison group (properties situated within 5-10 km of monitoring stations).

However, we argue that our results are less susceptible to such overestimation bias, as our comparison is conducted within a 10-kilometer vicinity. This means that any county-level or region-level regulatory changes would likely affect both houses within a 5-kilometer radius and those within a 5 to 10-kilometer radius. To further verify our findings and mitigate potential bias, we conduct the baseline estimation using a subsample limited to counties not designated as *nonattainment*. As presented in Column 1 of Appendix Table 1, the estimate price effects closely resemble our baseline results.[17]

Placebo Tests

To further validate our baseline results, we conduct two placebo tests. First, we assign each monitoring station a placebo establishment date that precedes its actual establishment date by three years. We then estimate Equation (1) and present the regression results in Table 5 Column 1. The estimate for the price effects is both statistically insignificant and of a small magnitude. This suggests that house prices within and beyond 5 kilometers of the monitoring station exhibit parallel trends before the actual establishment of the monitoring station, providing robust support for our baseline findings.

Second, we use houses located within 5 to 10 kilometers of the monitoring station as the placebo treatment group and observe negligible price effects. The comparison group in this analysis includes houses located within 10 to 15 kilometers of the same monitoring station. As shown in Column 2, the estimated price effects are statistically insignificant.

Relocation of Facilities to Areas in the Comparison Group

[17] Price effects of the monitoring station's establishment are also evident in *nonattainment* counties, as shown in Column 2, where we restrict the estimation sample to counties designated as *nonattainment*.

In response to the establishment of a monitoring station nearby, firms may opt to shift their production to areas beyond the regulator's reach (i.e., areas farther away from the monitoring station) in an effort to minimize compliance costs. Such firm relocations are likely to exert downward pressure on house prices in the comparison group (Currie et al., 2015), potentially resulting in an overestimation of our estimated price effects.

Our identification setting reduces the susceptibility of the estimated price effects to such bias. For example, we note that firms incur relocation costs and will relocate only if the benefits, derived from lower compliance costs and reduced compliance risks, outweigh the relocation expenses. Given this context, it is less likely that firms would choose to relocate to areas situated only 5 to 10 kilometers away within the same vicinity. Nevertheless, we conduct various robustness analyses to address this overestimation concern. Specifically, we estimate a regression using a sample that excludes comparison areas where the aggregate number of industrial facilities increased after the monitoring station's establishment. As shown in Column 1 of Table 6, the estimated price effect closely resembles the baseline estimate in terms of direction, statistical significance and magnitude. We further incorporate facility-level emissions information and exclude areas where the aggregated amount of air emissions (Column 2), water emissions (Column 3), land emissions (Column 4), and total emissions (Column 5) in the comparison areas increased following the monitoring station's establishment. Results remain consistent across all subsample analyses.

3.4 Heterogeneity in the Price Effect

Quantile Treatment Effects

The disproportionate exposure to environmental hazards, particularly among economically disadvantaged groups and racial minorities, is widely documented and continues to garner attention within communities (Banzhaf, Ma and Timmins, 2019; Christensen and Timmins, 2022; Dominici et al., 2022; Currie, Voorheis and Walker, 2023). Thus, the value created by the monitoring station network could potentially have a greater impact on economically disadvantaged groups. To explore this further, we estimate a quantile treatment effects regression model to examine how the establishment of monitoring stations affects different quantiles of the housing price distribution.

The estimation of unconditional quantile treatment effects of the monitoring station's establishment involves two steps (Haupt and Wiborg, 2021). The treatment variable is first regressed on all control variables and fixed effects included in Equation (1). The outcome variable, housing prices, is then regressed on the residualized treatment variable using the Conditional Quantile Regression algorithm (Koenker and Bassett, 1978; Borgen, Haupt and Wiborg, 2021).

Figure 4 presents the average treatment effect of monitoring station establishment on various house price quantiles. The estimates suggest that the most pronounced price effects of monitoring station establishments manifest within the lower deciles of the housing price distribution, particularly within the first and the fourth decile. Notably, there is a substantial increase of approximately 4.6% in house prices in the first decile and 3.8% in the second decile following the establishment of monitoring stations. The third and fourth deciles similarly experience an increase of approximately 2%. Price effects are muted for houses falling within the fifth decile and above, which may be attributed to the likelihood that higher-income individuals residing in these residences already possess the resources needed to mitigate their exposure to poor air quality, consequently diminishing the capitalization of new local air quality monitoring.

These findings carry important implications, particularly for economically disadvantaged individuals and communities. The substantial increase in house prices among the lower deciles of the housing price distribution signifies that the establishment of monitoring stations predominantly benefits those with more limited financial resources, as they are more likely to reside in housing within these lower deciles.[18] This outcome underscores the potential of monitoring stations to mitigate pollution disparities among economically disadvantaged individuals, thereby contributing to improved environmental equity.

Heterogeneity by Monitoring Intensity

Due to the high operating costs associated with the procurement, operation, and maintenance of PM monitoring stations, these stations may be granted permissions to monitor pollutants on an intermittent basis. Consequently, this results in cross-sectional variation in the monitoring frequencies across stations. Some monitoring stations may adhere to a 1-in-6-day schedule, others may follow a 1-in-3-day schedule, and some may conduct motoring every day.

The monitoring schedule is published on the EPA's website one year in advance. The combination of intermittent monitoring and the early release of the monitoring schedule may induce firms to strategically reduce emissions during monitored days while increasing emissions during unmonitored days (Zou, 2021). Therefore, it is anticipated that monitoring stations adhering to an everyday sampling schedule will possess the highest level of environmental oversight, thereby generating the most substantial value for the surrounding communities, which can then be reflected in housing prices.

To examine the heterogeneity in price effects by monitoring intensity, we estimate separate regressions for two subsamples: one comprising daily monitors and the other consisting of non-daily monitors. The estimated price effects for these subsamples are presented in Table 7,

[18] We confirm these findings by performing heterogeneity analyses based on zip code characteristics, utilizing median household income and median per capita income data obtained from 2015 American Community Survey (ACS) 5-year estimate. We classify zip codes into two groups: those with incomes higher than median and those with incomes lower than median. While the difference in coefficients is statistically insignificant, we do observe larger point estimates of price effects for houses in more economically disadvantaged areas—houses in zip codes with lower median household income and lower per capita income (Appendix Table 2).

Columns 1 and 2, respectively. The point estimate of the price effects of daily monitors is 0.017, approximately 42% larger than the estimate for the full sample. Conversely, the price effects of nondaily monitors are relatively smaller, providing suggestive evidence that daily monitors exhibit a higher level of environmental oversight and, consequently, yielding more favorable environmental outcomes.

Heterogeneity by Pollution Level

The price effects associated with the establishment of monitoring stations may vary cross-sectionally based on the pollution levels in the respective areas. Areas exposed to elevated pollution levels may experience more pronounced price responses, as these areas are more susceptible to heightened regulatory scrutiny and targeted enforcement interventions aimed at mitigating environmental impact. To empirically examine this aspect, we regress $Ln(Price)_{it}$ on the interaction of the price effect measure, $After_t \times \mathbb{1}[\text{Distance}_\text{i} < 5\text{km}]$, with empirical proxies for areas exposed to higher pollution levels and areas exposed to lower pollution levels, as illustrated in the following equation:

$$Ln(Price)_{it} = \beta_1 After_t \times \mathbb{1}[\text{Distance}_\text{i} < 5\text{km}] \times \mathbb{1}[High\ Pollution\ Areas] + \beta_2 After_t \times \mathbb{1}[\text{Distance}_\text{i} < 5\text{km}] \times \mathbb{1}[Low\ Pollution\ Areas] + X_{it}\phi + \lambda_z + \theta_{mt} + \varepsilon_{it} \quad (2)$$

We measure the pollution levels of localities using various pre-establishment pollution indicators. Our first indicator is the concentration of polluting activities in an area, determined by the number of industrial facilities reported in the Toxic Release Inventory within a 10-kilometer radius of the monitoring station in the year prior to the station's establishment. We categorize the measure of pollution level into four quantiles, considering areas with numbers exceeding the median as *high-pollution areas* and those with numbers lower than the median as *low-pollution areas*.

Column 1 of Table 8 shows a significant and positive price effect of monitoring station establishment in *high-pollution areas*, while price effects in *low-pollution areas* are small and statistically insignificant. In Columns 2 and 3, we find consistent results when we repeat the same estimation using the total amount of toxic releases and the total amount of toxic air releases as the measure of pollution level. These findings suggest that housing prices in highly polluted areas increase by at least 1.4% after the establishment of a monitoring station.

4. Mechanisms

We now explore two potential mechanisms through which the establishment of a monitoring station can influence property prices. Firstly, firms may engage in extensive efforts to evade regulatory oversight due to the substantial costs associated with regulatory compliance, as documented in a growing body of literature (Vollard, 2017; Zou, 2021; Alexander and Schwandt, 2022; Agarwal et al., 2023). This gives rise to the role of monitoring stations as compliance enforcement tools for ensuring that industrial facilities comply with existing environment regulations, thus preventing the release of unauthorized emissions (Axbard and Deng, 2024). Consequently, this contributes to improved air quality, and subsequently, higher property prices. We refer to the first mechanism as the *Improved Air Quality Channel*.

Second, air quality data from monitoring stations provides prospective home buyers with *new* information about the air quality in the area. Building on existing literature that highlights how a lack of information can lead to market inefficiency and the importance of information disclosure in overcoming market failure, the new disclosure of air quality information following the establishment of a monitoring station serves as a shock that corrects any incomplete information between buyers and sellers, thereby affecting transaction prices

(Mastromonaco, 2015; Frondel, Gerster and Vance, 2020; Myers, Puller and West, 2022). We refer to the second mechanism as the *Information Channel.* We explore these mechanisms in the following section.

4.1 Improved Air Quality

Firms Emissions

We first examine whether the estimated increase in property prices following the establishment of a monitoring station is attributed to firms' strategic response to heightened environmental oversight, resulting in improved air quality in the locality around the monitoring station. While earlier findings that show larger price effects in areas with higher levels of pollution provide suggestive evidence supporting this mechanism, we undertake a more in-depth examination using firm-level emissions data. Specifically, we utilize detailed geographic data from the facility-level annual emission records obtained from TRI. We calculate the distances of these facilities to the monitoring stations, and we categorize facilities located within the 5-kilometer radius of the monitoring station as those directly exposed to increased environmental oversight. We estimate

$$Ln(Emissions)_{idt} = \beta After_t \times \mathbb{1}[\mathrm{Distance_i} < 5\mathrm{km}] + \gamma_i + \theta_{dmt} + \varepsilon_{idt} \quad (3)$$

where the dependent variable is the natural logarithm of the annual emission measure of facility i in industry d in year t. Specifically, with the inclusion of industry × monitoring station × year fixed effects, θ_{dmt}, we compare the annual emissions of *exposed* facilities to facilities situated within a 5 to 10-kilometer radius of the same monitoring station and in the same industry sector.[19] This identification strategy controls for time-invariant heterogeneity across

[19] We use 6-digit North American Industry Classification System (NAICS) code, also available in the TRI data.

facilities and at the same time accounts for any industry-level and regional-level shocks that may influence facilities' productions or emissions.

Column 1 of Table 9 presents the effects of monitoring station establishment on a facility's *Total Emissions*, which is the total quantity of toxic chemicals released on-site to air, water, and land. We observe a statistically significant reduction in total emissions by facilities subjected to increased environmental oversight. These *exposed* facilities reduce their total on-site emissions released by approximately 46.7% (or 126,530 pounds = 59,089 × 46.7%) following the establishment of a nearby monitoring station, in comparison to facilities located farther away from the monitoring station. These results remain consistent when we compare the *exposed* facilities to either facilities within a 5 to 10-kilometer radius of any monitoring stations in the same state (Panel B) or facilities within a 5 to 10-kilometer radius of any monitoring stations in the same county (Panel C).

Given that the stations we study are air quality monitoring stations that monitor fine particulate matter rather than water or soil quality, we should expect that the estimated reductions in total emissions are primarily driven by reductions in emissions through air, while emissions through water and land remain unaffected. In particular, we exploit regressions on water and land emissions as a useful placebo test to examine whether the estimated reduction in emissions presented in Column 1 is primarily attributable to facility-specific shocks that are unrelated to the establishment of a monitoring station but may influence overall production and, consequently, emissions. To conduct this test, we replace the dependent variable in Equation (3) with total air emissions, total water emissions, and total land emissions in Columns 2, 3, and 4, respectively.[20] The results show that e*xposed* facilities experience a significant reduction

[20] In Columns 2 to 5 of Appendix Table 3, we aggregate the annual emissions at the monitoring station and distance level (within 5 kilometers or within 5 to 10 kilometers of a monitoring station) and perform the same regressions using the aggregated amount of emissions as the dependent variable. Results are consistent with the findings obtained from regressions at the facility level.

of approximately 47.3% in total air emissions, whereas total water and land emissions exhibit minimal response, both statistically and economically.

In Figure 5, we illustrate the dynamic effects on air emissions across three specifications. Throughout all specifications, variations in the levels of air emissions in the pre-establishment years, relative to Year -3, consistently hover around zero, both numerically and statistically. However, a notable reduction is observed in the first year following the opening of the monitoring station. Subsequent years show incremental reductions, suggesting a prompt adaptive response by firms to heightened regulatory scrutiny as a strategic measure to mitigate regulatory costs.

We next examine the extensive margin of facilities' response to the establishment of a monitoring station. We separately calculate the annual number of the TRI facilities located within the 5 kilometers and within 5 to 10 kilometers of the radius of a monitoring station in the year. We then regress the natural logarithm of the total number of facilities on an indicator for whether the facility is located within 5-kilometer radius of a monitoring station and its interaction with an indicator representing years after the monitor's establishment.

As presented in Column 1 of Appendix Table 3, we observe a 2.6% reduction in the total number of facilities within a 5-kilometer radius of a monitoring station following its establishment. These results complement our earlier findings. Taken together, they suggest that enhanced environmental oversight facilitated by monitoring stations deters firms' emissions both on the intensive and extensive margins, consequently enhancing values for properties in the vicinity.

Satellite Measure of Particulate Pollution

The comparison of air quality before and after the establishment of a monitoring station was previously infeasible due to the unavailability of air quality data predating the station's establishment. To circumvent this limitation, we utilize a daily-level satellite measure of atmospheric particle pollution, known as aerosol optimal depth (AOD), measured at a spatial resolution of 10 kilometers × 10 kilometers. This allows us to investigate the impact of monitoring station establishment on the air quality in the vicinity of the monitoring station. Specifically, we estimate the following equation:

$$Ln(aerosol)_{gt} = \beta After_t \times \mathbb{1}[Monitoring\ Station]_g + \gamma_g + \theta_t + X_{gt}\phi + \varepsilon_{gt} \qquad (4)$$

where the dependent variable is the natural logarithm of AOD at grid g at time t. The primary variable of interest is the air quality impact of a monitoring station's establishment, depicted by the interaction between an indicator for post-establishment and an indicator for the grid where a monitoring station is located. We include grid fixed effects, γ_g, to account for unobservable cross-sectional time-invariant differences among grids. To control for variations in economic activities and, consequently, pollution concentration across different years, as well as the presence of seasonality patterns, we include time fixed effects encompassing year, month-of-year, and day-of-week fixed effects (θ_t). In addition, as the measure of pollutant concentration could be influenced by meteorological factors, we include weather controls, X_{gt}, including daily maximum and minimum temperatures categorized into 5-degree bins, as well as precipitation categorized in 5-millimeter bins.

The regression results are presented in Table 10. As shown in Column 1 of Panel A, the aerosol concentration in the vicinity of a monitoring station experiences a 3.1% reduction following its establishment. The magnitude of this negative impact amplifies with the extension of the post-establishment window in the estimation sample: aerosol concentration decreases by 3.7%, 5.1% and 7.5% when considering a 5-year post-establishment window, 10-year post-establishment window, and entire sample, respectively.[21] These estimated effects remain robust across various specifications, including interacting the time fixed effects with state fixed effects and substituting the time fixed effects with a more stringent date fixed effects.

The magnitude of effects on aerosol concentration is considerably smaller than the estimated effects on facility-level emissions, and this difference can potentially be explained by three reasons. Firstly, the satellite measure of aerosol concentration is recorded at a spatial resolution of 10 kilometers × 10 kilometers, which is a relatively coarse measure, considering the highly localized effect of monitoring stations, as documented by the decaying effect presented in Appendix Figure 2. Secondly, the satellite measure represents a snapshot of pollution in each area at approximately 10:30 a.m. local time every day, which may not capture emissions or production activities that occur at other times. Thirdly, the satellite measure captures aerosol conditions in the entire column of air from its viewpoint 700km above ground, and as pollutants can travel over large distances, the estimated effects are likely to be attenuated.

Nevertheless, these results supplement our earlier findings on the impacts of monitoring station's establishment on firm-level emissions. Together, our results align with the research of Axbard and Deng (2024) which demonstrates increased enforcement activities directed at firms in proximity to monitoring stations and improved air quality following their opening. By examining both firm-level emissions and aggregate air quality measured via satellite, we provide complementary evidence supporting monitoring stations as an effective environmental regulatory tool, facilitating environmental conveyance and leading to improved environmental outcomes, which are then reflected in property values.

[21] The increased magnitude may be attributed to the influence of environmental regulation affecting specific areas subsequent to the installation of a monitoring station, potentially leading to an overestimation of the station's impact.

4.2 Information Channel

Barwick et al. (2023) demonstrate that the dissemination of air quality information increases public awareness of air pollution, resulting in behavioral shifts such as avoiding outdoor pollution exposure and increased spending on protective products. In this section, we investigate whether the estimated price effects are driven by the availability of *new* information on air quality following the establishment of a monitoring station, as the *new* information may alter the perceptions of local pollution levels among prospective property buyers and sellers, thereby potentially influencing transaction prices.

To examine the *Information Channel*, we begin by identifying subsets of areas where this mechanism is likely to have a pronounced effect—areas where the *actual* air quality diverges from the *perceived belief* about air quality. The underlying assumption is that, if the *Information Channel* is the sole mechanism at play, the establishment of a monitoring station would update people's belief regarding air quality in the area, consequently, property prices may potentially increase (decrease) in areas where the monitoring station reveals a lower (higher) level of air pollution than previously perceived. In contrast, property values are expected to remain unaffected in areas where the *actual* air quality obtained from the monitoring station aligns with the *perceived belief* about local air pollution levels.

We proxy for the *perceived belief* about local air pollution levels using the number of industrial facilities within a 10-kilometer radius of the monitoring station one year before the station's establishment. This follows the idea that individuals gauge local pollution levels based on the proximity or concentration of pollution sources in the absence of monitoring stations that provide air quality information. We subsequently classify areas into two distinct groups: *perceived* low-pollution areas and *perceived* high-pollution areas, depending on whether the proxy falls below or above the sample median.

To proxy for the *actual* local air pollution levels, we utilize the daily PM 2.5 values recorded by the monitoring station averaged over the first year of its opening. Similarly, we categorize areas into two groups: *actual* low-pollution areas and *actual* high-pollution areas, based on whether the proxy is below or above the sample median.

Finally, using these two proxies, we classify areas into four distinct groups: those with *perceived* low pollution and *actual* low pollution (LL) levels, those with *perceived* high pollution and *actual* high pollution (HH) levels, those with *perceived* low pollution and *actual* high pollution (LH) levels, and those with *perceived* high pollution and *actual* low pollution (HL) levels. If the *Information Channel*, rather than the *Improved Air Quality Channel*, is the primary driver of the estimated price effects, we would expect to observe no price effect for those located in LL and HH groups, and a decrease (increase) in prices for those located in LH (HL) groups.

Table 11 presents the regression estimates of price effects derived from Equation (1) using subsamples of areas in LL, LH, HL, and HH, respectively. Focusing on the subsamples of properties in areas with no disparity between *perceived* and *actual* air quality information, namely LL and HH, we observe no changes in property prices for those located in LL but statistically significant and positive price effects in properties located in HH. This result is inconsistent with the *Information Channel* but closely aligns with the *Improved Air Quality Channel*, where the positive price effects are likely driven by expected or observed improvement in air quality following the opening of the monitoring station. Turning to the subsamples of properties in LL and HL, where there are disparities between *perceived* and *actual* air quality information, we observe statistically significant price effects in properties located in HL. However, we note a positive, though insignificant, effect on prices of properties in LH, which is, again, inconsistent with the *Information Channel* that predicts negative price effects for properties located in HL.[22]

There are several limitations to consider. The first limitation concerns the use of post-establishment values of PM 2.5 as the proxy for the *actual* local pollution level. This approach introduces the possibility of confounding factors, as the post-treatment pollution level might be influenced by the treatment itself. Second, the estimated effects obtained in the subsample analyses reflect the net effects on property prices and can be interpreted by two forces. Taking the positive price effects in HL as an illustration, the first force is that property values increase as people realize that the pollution levels are lower than previously perceived, and hence, incorporating this *positive* information in transaction prices. Alternatively, positive price effects may reflect improved air quality due to reduced emissions from nearby industrial facilities after the establishment of the monitoring stations. It is challenging to disentangle these two mechanisms. Nonetheless, considering estimated price effects from all subsample regressions, we can reject the possibility that the *Information Channel* is the sole mechanism driving the positive price effects of monitoring stations establishment.

To complement the above analysis, we explore the price effects associated with the establishment of non-regulatory monitoring stations, where the reported values are not employed for regulatory purposes but rather for disclosing daily Air Quality Index values.[23] The presence of these monitoring stations is less likely to influence polluters' emissions behavior and, consequently, air quality, given that their primary purpose is non-regulatory. Nonetheless, they could impact house prices if participants in the real estate market respond to

[22] The estimated effects using these subsamples remain robust when using shorter post-establishment sample windows of 6 months or 1 year, or when employing total air emissions surrounding the monitoring station as an alternative proxy for *perceived* belief about air pollution levels, as shown in Appendix Figure 3.
[23] The main analyses in the paper focus on only regulatory monitors—that are, 88101 monitors. See, https://www.epa.gov/outdoor-air-quality-data/what-difference-between-parameter-codes-88101-and-88502-pm25-monitors, for more information.

the availability of *new* air quality information. This offers an alternative approach to disentangle the two mechanisms.[24]

As shown in Appendix Table 4, across all specifications, we find that house prices exhibit no change after the establishment of a nearby non-regulatory monitoring station, suggesting that air quality information, when not intended for regulatory purpose, may not influence property prices. However, the subdued response represents the net price effects that could be simultaneously driven by both *positive* information (*perceived* high pollution areas, being in fact, *actual* low pollution areas) and *negative* information (perceived low pollution areas being, in fact, *actual* high pollution areas), exerting opposing effects on property prices. To further investigate this, in Appendix Table 5, we replicate the subsample analyses presented in Table 11 using the sample of non-regulatory monitoring stations. All estimates are statistically insignificant; while price effects in LH areas are in the negative direction, price effects in HL areas are also negative, contrary to the prediction of the *Information Channel*.

Both analyses—the initial one utilizing subsample analyses and the subsequent one exploring non-regulatory monitoring stations—are subject to their own limitations. Therefore, we regard these estimates not as definitive but rather as suggestive indications that the *Information Channel* may be a trivial factor in driving the baseline price effects.

5. Conclusion

This paper examines the effect of monitoring stations establishment on housing prices, facility-level emissions and air quality, focusing on the nationwide opening of particulate matter monitoring stations in the United States. We find that the establishment of monitoring stations leads to a 1.1% increase in the values of properties located near the stations, and the price

[24] We may fail to disentangle the two mechanisms if individuals believe that air quality data provided by non-regulatory monitors could be used to complement regulatory actions and hence firms react to the opening of these stations.

effects are mainly driven by improved air quality in the locality as evinced by the reduction in emissions by facilities and hence aerosol concentration. These findings suggest that monitoring networks can serve as effective conveyance tools to discourage unauthorized emissions by firms, thereby augmenting the efficacy of existing environmental regulations.

To assess the overall value generated by these monitoring stations, we perform a back-of-the-envelope calculation. We first estimate the total number of housing units *affected* by the establishment of monitoring stations, drawing on data from the 2020 American Community Survey (ACS) at the block-group level. This involves the identification of block groups within a 5-kilometer boundary of any particulate matter monitoring stations using a Geographic Information System (GIS) software. Subsequently, we aggregate the total number of housing units in these *affected* block groups. Considering that some block groups may not be entirely encompassed by the 5-kilometer boundary, we apply a conservative estimate by halving the aggregate number of housing units (35,140,312), yielding a total of 17,570,156 housing units. Utilizing the estimated baseline price effects of 1.1% and the average prices of *affected* houses before opening of monitoring stations ($271,011 in 2020 dollars), the total value creation in the housing market amounts to $52,378,761,024 (17,570,156 × $271,011 × 1.1%).

Efficiently designing environmental regulations remains a subject of ongoing debate. On one hand, environmental advocates often express concern about the scarce distribution of monitoring networks; on the other hand, policy regulators grapple with the high operational costs associated with these networks, particularly for conveyance tools such as physical inspections and monitoring stations. According to the EPA's 2012 estimate of the total costs incurred for the monitoring program by the EPA in 2012, the annual cost of operating the entire particulate matter monitoring network in the country exceeds $58 million in 2020 dollars. Our paper contributes valuable insights by suggesting that a portion of these costs can be offset by the resulting increase in housing values, in addition to the health and environmental benefits resulted from improved air quality. These findings have important policy implications, suggesting the potential use of low-cost monitoring methods or satellite data for regulatory purposes assessing environmental regulation compliance, rather than relying solely on data from fixed-point monitoring sources.

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Figure 1. Geographical Distribution of PM Monitoring Stations

This figure presents the geographical distribution of particulate matter monitoring stations (depicted in black), superimposed on the satellite measure of averaged daily aerosol concentration (scaled by × 0.001) at a spatial resolution of 10km × 10km in 2000 across the continental United States.

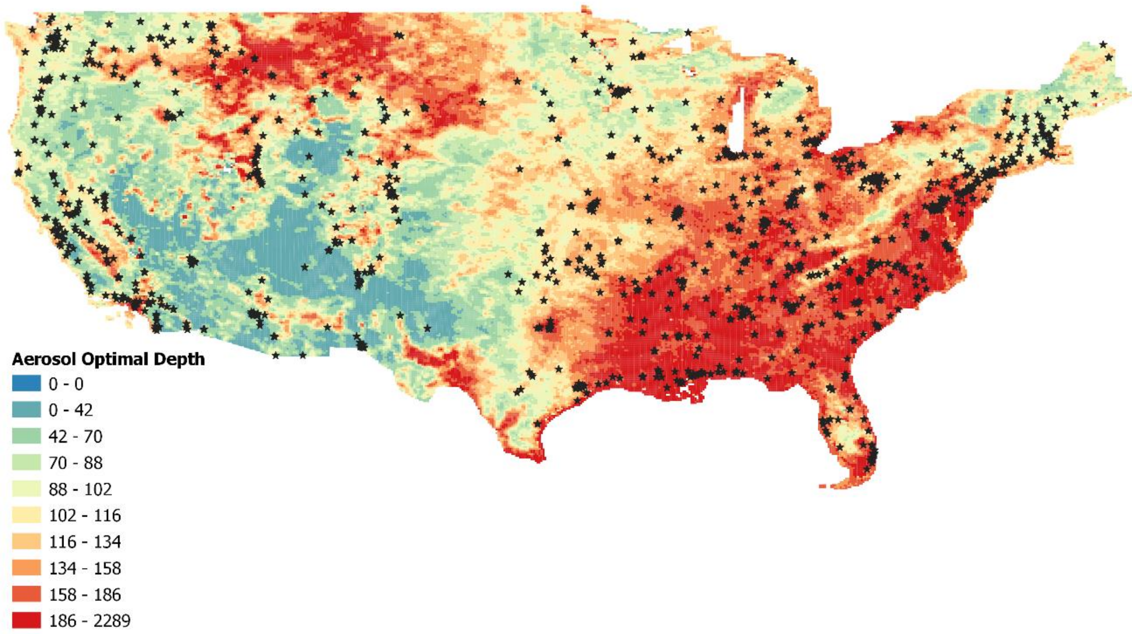


Figure 2. Number of Monitoring Station Establishments by Year

This figure shows the total number of particulate monitor monitoring stations established over the years.

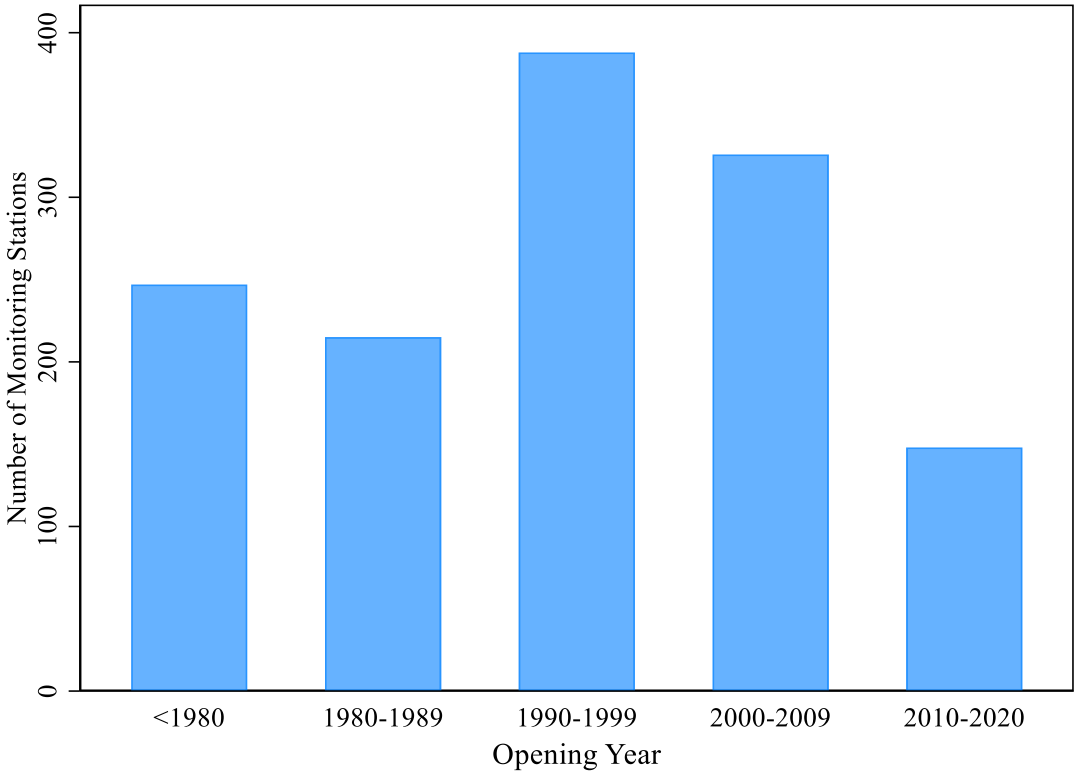


Figure 3. Dynamic Effect of Monitoring Station Establishments on Housing Prices

This figure shows coefficient estimates of price effects from the regression of log transaction prices on $\mathbb{1}[\text{Distance}_i < 5\text{km}]$ interacted with a set of time period dummies that indicate the number of quarters before and after the establishment of a monitoring station. The sample is restricted to transactions of properties within 10 kilometers of a monitoring station and 12 quarters (or 3 years) before or after the station's establishment. The regression includes all property and transaction controls, zip code fixed effects and monitoring station × Sale Year-Month fixed effects. Quarter −12 is the omitted reference period while Quater 1 is the first quarter in which the monitoring station opened. Ninety-five percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the zip code level.

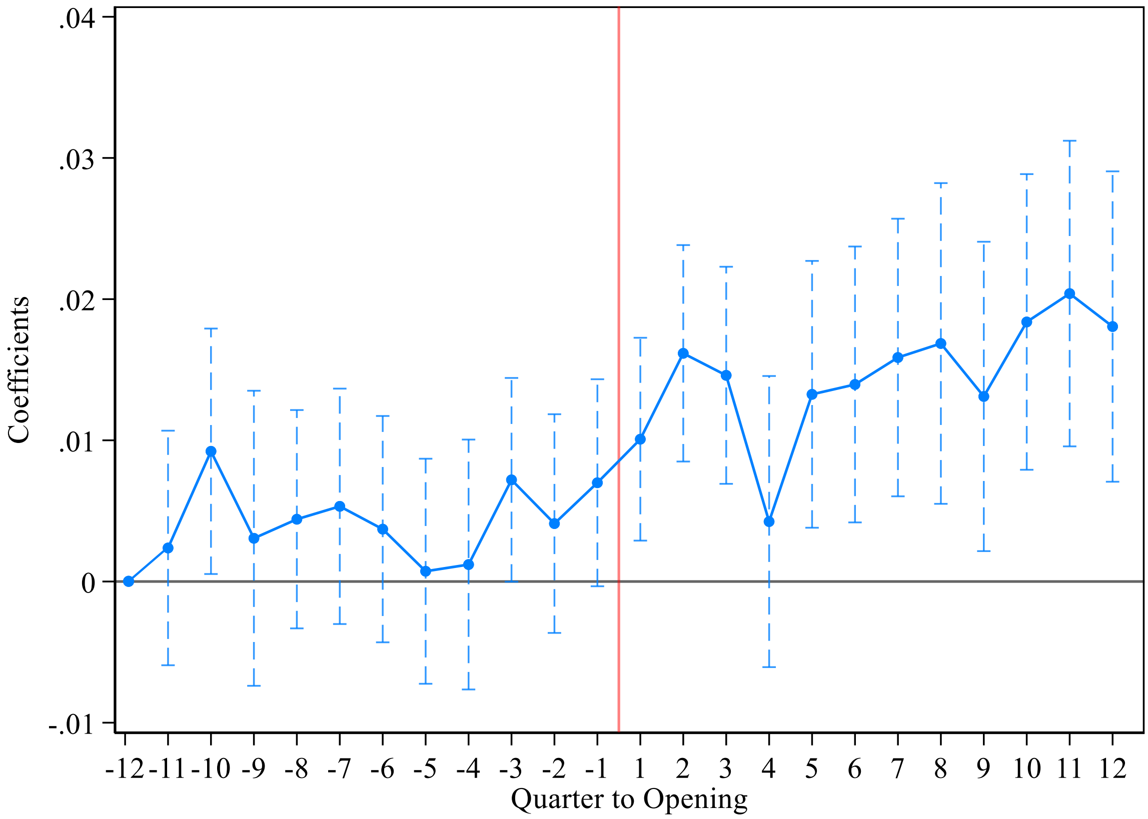


Figure 4. Quantile Treatment Effects of Monitoring Station Establishments on House Prices

This figure presents the effects of monitoring station on various quantiles of the housing price distribution. Each line represents a point estimate and a 95% confidence interval from a quantile regression of log transaction prices at *q* decile on the interaction between an indicator for transactions occurring after the station's establishment and an indicator for houses located within 5 kilometers of a monitoring station. The sample is restricted to transactions of properties within 10 kilometers of a monitoring station and 3 years before or after the station's establishment. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. Standard errors are clustered at the zip code level.

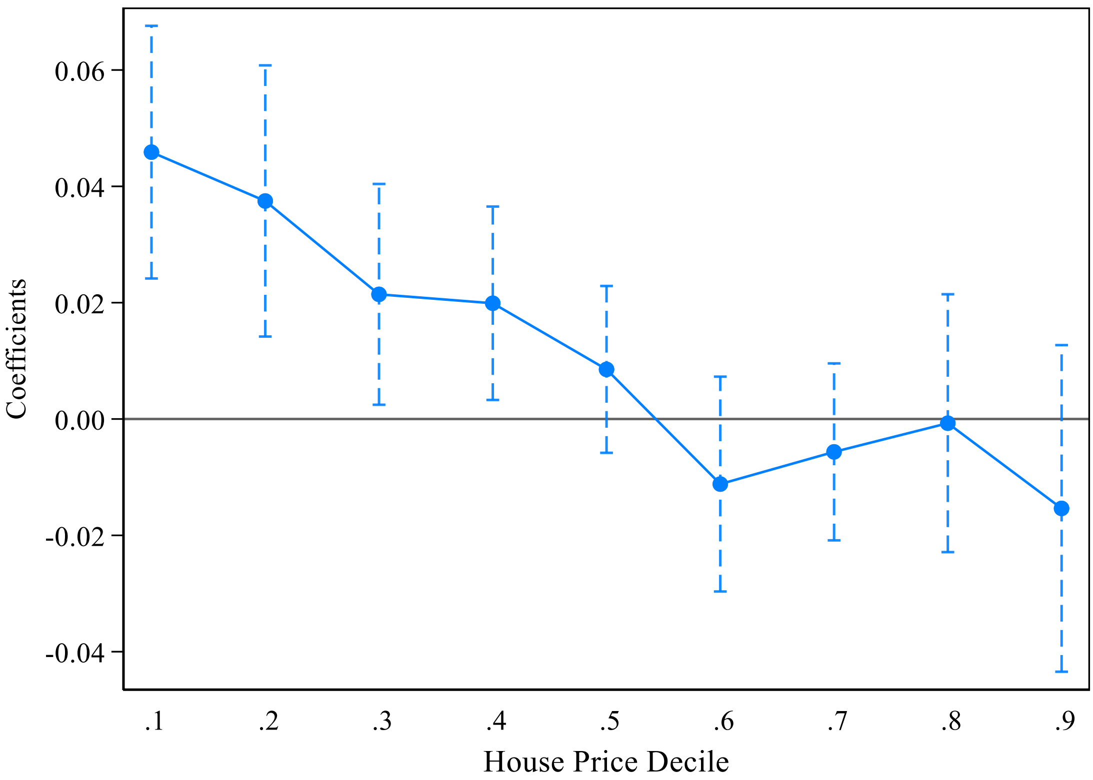


Figure 5. Dynamic Effect of Monitoring Station Establishments on Air Emissions

This figure shows coefficient estimates of effects from the regression of log amount of firm-level air emissions on $\mathbb{1}[\text{Distance}_i < 5\text{km}]$ interacted with a set of time period dummies that indicate the number of years before and after the establishment of a monitoring station. The sample is restricted to air emissions reported by facilities located within 10 kilometers of a monitoring station 3 years before and 3 years after the station's establishment. Year −3 is the omitted reference period while Year 1 is the first year in which the monitoring station opened. The upper panel includes facility (F) fixed effects and Industry (Ind) × Monitoring Station (M) × Year (Y) fixed effects; the middle panel includes facility (F) fixed effects and Industry (Ind) × State (S) × Year (Y) fixed effects; the bottom panel includes facility (F) fixed effects and Industry (Ind) × County (C) × Year (Y) fixed effects. Ninety-five percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the industry level.

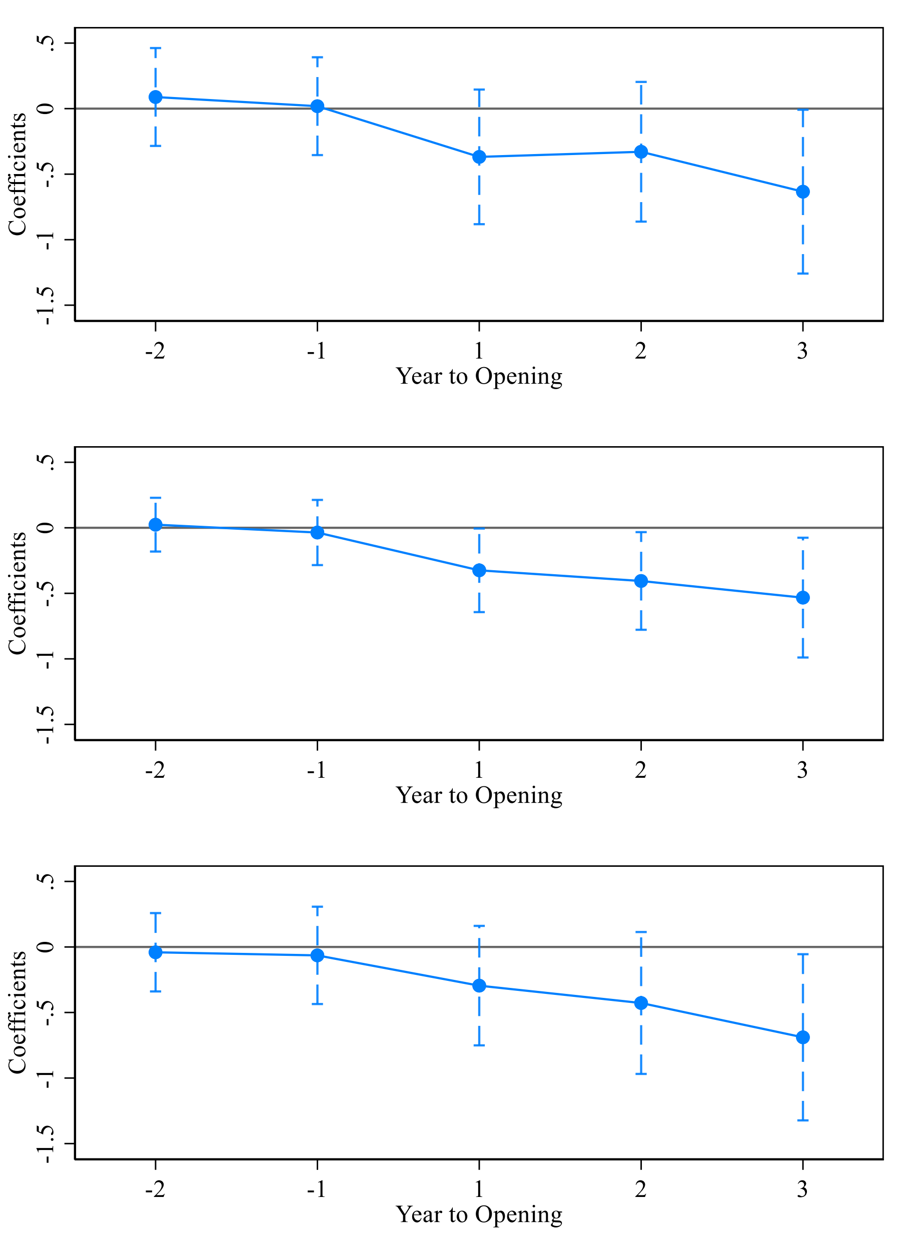


Table 1. Summary Statistics

This table presents summary statistics for the key variables of control and interest in our baseline sample covering the period between 1995 and 2020 for the CoreLogic dataset. Panel A presents summary statistics for the entire baseline sample, while Panel B breaks down summary statistics for properties located within 5 kilometers of a monitoring station and those within 5 to 10 kilometers of a monitoring station. Properties are restricted to those located within 10 kilometers of a monitoring station transacted 3 years before or after the station's establishment.

Panel A: Full Sample

	(1) Obs.	(2) Mean	(3) Std. Dev.	(4) P25	(5) P50	(6) P75
House Price ($1000s)	3,822,505	221.89	190.87	104.50	164.28	275.00
# Bedrooms	3,822,505	3.07	0.97	3.00	3.00	4.00
# Bathrooms	3,822,505	2.18	0.95	2.00	2.00	3.00
Property Age (yrs)	3,822,505	34.12	29.09	10.00	28.00	52.00
Building Sq. Ft.	3,822,505	1,710.74	797.52	1,168.00	1,522.00	2,037.00
Land Sq. Ft.	3,822,505	18,429.33	77,378.11	4,863.00	7,186.00	11,015.00
Pool (d)	3,822,505	0.07	0.26	0.00	0.00	0.00
Mobile Home (d)	3,822,505	0.00	0.06	0.00	0.00	0.00
Cash Purchase (d)	3,822,505	0.10	0.30	0.00	0.00	0.00
Resale (d)	3,822,505	0.91	0.29	1.00	1.00	1.00
Corporate Buyer (d)	3,822,505	0.63	0.48	0.00	1.00	1.00
Owner Occupied (d)	3,822,505	0.81	0.39	1.00	1.00	1.00
Distance to Monitor (km)	3,822,505	5.75	2.43	3.84	5.95	7.82

Panel B: Samples by Distance to Monitoring Stations

	< 5 km			5 – 10km		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
House Price ($1000s)	1,466,647	210.96	182.84	2,355,858	228.69	195.40
# Bedrooms	1,466,647	3.04	1.00	2,355,858	3.09	0.94
# Bathrooms	1,466,647	2.10	0.93	2,355,858	2.23	0.96
Property Age (yrs)	1,466,647	37.22	30.91	2,355,858	32.18	27.72
Building Sq. Ft.	1,466,647	1,657.64	765.66	2,355,858	1,743.80	814.98
Land Sq. Ft.	1,466,647	14,912.93	52,072.56	2,355,858	20,618.47	89,522.38
Pool (d)	1,466,647	0.07	0.25	2,355,858	0.07	0.26
Mobile Home (d)	1,466,647	0.00	0.06	2,355,858	0.00	0.06
Cash Purchase (d)	1,466,647	0.10	0.30	2,355,858	0.10	0.30
Resale (d)	1,466,647	0.91	0.28	2,355,858	0.90	0.30
Corporate Buyer (d)	1,466,647	0.63	0.48	2,355,858	0.63	0.48
Owner Occupied (d)	1,466,647	0.79	0.40	2,355,858	0.81	0.39
Distance to Monitor (km)	1,466,647	3.14	1.22	2,355,858	7.38	1.34

Table 2. Baseline Regression Results

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. The explanatory variable of interest is After × Dist. < 5km, which takes the value of one for a property within 5 kilometers of a monitoring station and transacted after the station's establishment. The sample is restricted to sales of residential properties within 10 kilometers of a monitoring station that occurred 3 years before or after the station's establishment. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. Column 1 presents baseline results with property controls, transaction controls, neighborhood fixed effects represented by zip code (Z) fixed effects, and time fixed effects represented by monitoring station (M) × Sale Year-Month (YM) fixed effects. Columns 2 to 5 introduce additional interactions of the time fixed effects. Column 2 interacts time fixed effects with PT, Column 3 with PT and R, Column 4 with PT, R, and I, and Column 5 with all property and transaction controls, respectively. Columns 6 and 8 replicate the specifications of Columns 1, replacing neighborhood fixed effects with M, and Z and M, and substituting time fixed effects with Z × YM, and county (C) × YM, respectively. Columns 7 and 9 mirror the interaction of time fixed effects with property and transaction controls as reported in Column 4. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
After × Dist. < 5km	0.011***	0.010***	0.009***	0.010***	0.039**	0.008**	0.007**	0.009***	0.008***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.018)	(0.003)	(0.003)	(0.003)	(0.002)
Observations	3,822,505	3,816,505	3,810,188	3,795,293	107,298	3,795,377	3,620,207	3,822,033	3,796,252
Adj R-squared	0.816	0.825	0.826	0.835	0.957	0.828	0.856	0.816	0.835
Neighborhood FE	Z	Z	Z	Z	Z	M	M	Z, M	Z, M
Time FE	M × YM	M × YM × PT	M × YM × PT × R	M × YM × PT × R × I	M × YM × (All Prop. & Trans. Controls)	Z × YM	Z × YM × PT × R × I	C × YM	C × YM × PT × R × I
Prop. & Trans. Controls	Y	Y	Y	Y	N	Y	Y	Y	Y
Distance Bin FE	Y	Y	Y	Y	Y	Y	Y	Y	Y

Table 3. Robustness to Alternative Specifications

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. The explanatory variable of interest is After × Dist. < 5km. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. Columns 1 to 6 correspond to their counterparts in Columns 1,4,6 to 9 of Table 2, respectively, which explore three geographical levels: zip code (Z), monitoring station (M), and county (C). The stacked difference-in-differences is applied by including interactions of both the treatment indicators (Distance Bin FE) and the time FE with monitoring station (M) fixed effects, using a sample restricted to sales of residential properties within 10 kilometers of a monitoring station that occurred 3 years before or after the station's establishment. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
After × Dist. < 5km	0.012***	0.010***	0.008***	0.006***	0.011***	0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	3,819,345	3,792,048	3,788,286	3,605,180	3,818,039	3,783,316
Adj R-squared	0.825	0.843	0.837	0.863	0.826	0.845
Neighborhood FE	Z	Z	-	-	Z	Z
Time FE	M × YM	M × YM × PT × R × I	M × Z × YM	M × Z × YM × PT × R × I	M × C × YM	M × C × YM × PT × R × I
M × Distance Bin FE	Y	Y	Y	Y	Y	Y
Prop. & Trans. Controls	Y	Y	Y	Y	Y	Y

Table 4. Robustness to Alternative Control Group and Sampling Periods

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. The explanatory variable of interest is After × Dist. < 5km. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. Columns 1 to 6 correspond to their counterparts in Columns 1,4,6 to 9 of Table 2, respectively, which explore three geographical levels: zip code (Z), monitoring station (M), and county (C). In Panel A, the comparison group is replaced with properties located within 10 to 20 kilometers of a monitoring station, and the sample consists of sales of residential properties within 5 kilometers or 10 – 20 kilometers of a monitoring station that occurred 3 years before or after the station's establishment. Panel B uses the baseline comparison group and a sample that includes sales of residential properties within 10 kilometers of a monitoring station occurring 3 years before or 5 years after the station's establishment. Panel C uses the baseline comparison group and a sample that includes sales of residential properties within 10 kilometers of a monitoring station occurring 3 years before or 1 year after the station's establishment. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Control Group [10km to 20km]						
After × Dist. < 5km	0.016***	0.015***	0.028***	0.022**	0.015***	0.013***
	(0.003)	(0.003)	(0.011)	(0.009)	(0.003)	(0.003)
Observations	6,102,714	6,073,842	6,043,355	5,750,858	6,100,801	6,066,349
Adj R-squared	0.829	0.848	0.844	0.873	0.830	0.850
Panel B: Sample Period [-3 to +5]						
After × Dist. < 5km	0.011***	0.010***	0.007**	0.006*	0.008***	0.007***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Observations	5,265,126	5,227,147	5,229,359	4,992,017	5,264,559	5,230,403
Adj R-squared	0.814	0.834	0.826	0.854	0.814	0.833
Panel C: Sample Period [-3 to +1]						
After × Dist. < 5km	0.007***	0.007***	0.008**	0.008***	0.006**	0.005**
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.002)
Observations	2,490,539	2,473,234	2,471,429	2,355,755	2,490,161	2,472,513
Adj R-squared	0.816	0.834	0.827	0.855	0.816	0.834
Neighborhood FE	Z	Z	M	M	Z, M	Z, M
Time FE	M × YM	M × YM × PT × R × I	Z × YM	Z × YM × PT × R × I	M, C × YM	C × YM × PT × R × I
Prop. & Trans. Controls	Y	Y	Y	Y	Y	Y

Distance Bin FE	Y	Y	Y	Y	Y	Y

Table 5. Placebo Tests

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. Column 1 tests the price effects by employing a placebo establishment date assigned to each monitoring station that precedes its actual establishment data by three years, using a sample of residential property sales within 10 kilometers of a monitoring station occurring 3 years before or after the station's establishment. Column 2 tests the prices effects by introducing a placebo treatment group, which comprises property sales within 5 to 10 kilometers, compared to a comparison group consisting of property sales within 10 to 20 kilometers. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) Placebo Treatment Timing	(2) Placebo Treatment Group
After × Dist. < 5km	0.002	
	(0.003)	
After × Dist. < 5-10 km		0.003
		(0.003)
Observations	2,856,908	4,970,969
Adj R-squared	0.816	0.834
Neighborhood FE	Z	Z
Time FE	M × YM	M × YM
Prop. & Trans. Controls	Y	Y
Distance Bin FE	Y	Y

Table 6. Subsample Analyses

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. The explanatory variable of interest is After × Dist. < 5km. The sample is restricted to sales of residential properties within 10 kilometers of a monitoring station that occurred 3 years before or after the station's establishment. Column 1 removes sales of properties located in the comparison areas (within 5 to 10 kilometers of a monitoring station) where number of TRI facilities increased after the station's establishment. Similarly, Columns 2 to 4 exclude sales of properties located in the comparison areas (within 5 to 10 kilometers of a monitoring station) where the total amount of reported emissions (e.g., air emissions, water emissions, land emissions, and total emissions) increased after the station's establishment. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) No. of TRI Facilities	(2) Air Release	(3) Water Release	(4) Land Release	(5) Total Release
After × Dist. < 5km	0.012***	0.009***	0.011***	0.011***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	3,459,681	3,392,156	3,361,488	3,490,718	3,347,188
Adj R-squared	0.815	0.812	0.815	0.815	0.812
Neighborhood FE	Z	Z	Z	Z	Z
Time FE	M × YM	M × YM	M × YM	M × YM	M × YM
Prop. & Trans. Controls	Y	Y	Y	Y	Y
Distance Bin FE	Y	Y	Y	Y	Y
Sample (Remove)	Comparison areas where no. of facilities or total emissions (E.g., air, water, land, total release) increased after treatment				

Table 7. Heterogeneity of Price Effects by Monitoring Intensity

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. The explanatory variable of interest is After × Dist. < 5km. The sample is restricted to sales of residential properties within 10 kilometers of a monitoring station that occurred 3 years before or after the station's establishment. Column 1 and 2 further restricts the sample to include sales of properties located near to monitoring stations with and without, respectively, at least one monitor that operates daily. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
After × Dist. < 5km	0.017***	0.006*
	(0.004)	(0.003)
Observations	1,553,955	2,194,685
Adj R-squared	0.831	0.802
Neighborhood FE	Z	Z
Time FE	M × YM	M × YM
Prop. & Trans. Controls	Y	Y
Distance Bin FE	Y	Y
Sample	Only Daily Monitors	Only Non-Daily Monitors

Table 8. Heterogeneity of Price Effects by Pre-Establishment Pollution Level

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. In Columns 1 to 3, 𝟙[Low Pollution Areas] is an indicator for properties situated in areas with a pollution level below the median, based on the number of TRI facilities, total amount of toxic emissions and total amount of toxic air emissions, respectively, in the area one year before the station's establishment . Similarly, 𝟙[High Pollution Areas] is an indicator for properties located in areas with a pollution level above the median. The sample is restricted to sales of residential properties within 10 kilometers of a monitoring station that occurred 3 years before or after the station's establishment. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) Number of TRI Facilities	(2) Total Release	(3) Air Emissions
After × Dist. < 5km × 𝟙[Low Pollution Areas]	0.003	0.004	0.005
	(0.005)	(0.005)	(0.005)
After × Dist. < 5km × 𝟙[High Pollution Areas]	0.014***	0.015***	0.014***
	(0.003)	(0.004)	(0.004)
Observations	3,822,505	3,822,505	3,822,505
Adj R-squared	0.816	0.816	0.816
Neighborhood FE	Z	Z	Z
Time FE	M × YM	M × YM	M × YM
Prop. & Trans. Controls	Y	Y	Y
Distance Bin FE	Y	Y	Y

Table 9. Effects of Monitoring Station Establishment on Facility-level Emissions

This table presents ordinary least squares estimates where the dependent variables are the natural log of one plus the annual amount of toxic release (Column 1), air release (Column 2), water release (Column 3), and land release (Column 4) reported by the facilities to the TRI. $After$ is an indicator for emissions reported after the establishment of a monitoring station and $Dist. < 5km$ is an indicator for facilities located within 5 kilometers of a monitoring station. The sample is restricted to emissions from facilities within 10 kilometers of a monitoring station occurring 3 years before or after the station's establishment. Panel A includes facility (F) fixed effects and Industry (Ind) × Monitoring Station (M) × Year (Y) fixed effects; Panel B includes facility (F) fixed effects and Industry (Ind) × State (S) × Year (Y) fixed effects; Panel C includes facility (F) fixed effects and Industry (Ind) × County (C) × Year (Y) fixed effects. The standard errors are clustered at the industry level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) Total Release	(2) Air Release	(3) Water Release	(4) Land Release
Panel A: Industry × Monitor × Year Fixed Effects				
After × Dist. < 5km	-0.467***	-0.473**	0.025	-0.213*
	(0.178)	(0.182)	(0.062)	(0.117)
Observations	7,724	7,724	7,724	7,724
Adj R-squared	0.863	0.868	0.890	0.686
Fixed Effects	F, Ind × M × Y	F, Ind × M × Y	F, Ind × M × Y	F, Ind × M × Y
Panel B: Industry × State × Year Fixed Effects				
After × Dist. < 5km	-0.324***	-0.362***	-0.009	-0.023
	(0.106)	(0.106)	(0.041)	(0.060)
Observations	13,203	13,203	13,203	13,203
Adj R-squared	0.861	0.867	0.887	0.709
Fixed Effects	F, Ind × S × Y	F, Ind × S × Y	F, Ind × S × Y	F, Ind × S × Y
Panel C: Industry × County × Year Fixed Effects				
After × Dist. < 5km	-0.405**	-0.386**	-0.019	-0.138
	(0.156)	(0.158)	(0.063)	(0.097)
Observations	8,462	8,462	8,462	8,462
Adj R-squared	0.862	0.866	0.892	0.705
Fixed Effects	F, Ind × C × Y	F, Ind × C × Y	F, Ind × C × Y	F, Ind × C × Y

Table 10. Effects of Monitoring Station Establishment on Grid-level Aerosol Concentration

This table presents ordinary least squares estimates where the dependent variables are the natural log of one plus the daily aerosol concentration scaled by 0.001 in each grid of 10 kilometers × 10 kilometers. $After$ is an indicator for aerosol concentrations reported after the establishment of a monitoring station in the grid and $Treated$ is an indicator for grids where a monitoring station is situated. Panel A includes Grid (G) fixed effects, Time (T) fixed effects that include Year, Month, and Day of Week fixed effects, and Weather (W) fixed effects that include fixed effects for daily maximum temperature bins, daily minimum temperature bins and daily precipitation bins. Panel B replaces the time fixed effects with State × Time (T) fixed effects and Panel C replaces the time fixed effects with date (D) fixed effects. Column 1 restricts the sample to the period 3 years before and after the monitoring station's establishment; Column 2 extends the post-establishment window to 5 years; Column 3 extends it to 10 years; and Column 10 employs the complete full sample. The standard errors are clustered at the grid level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) [-3, +3]	(2) [-3, +5]	(3) [-3, +10]	(4) Full Sample
Panel A: Time Fixed Effects				
After × Treated	-0.031**	-0.037***	-0.051***	-0.075***
	(0.013)	(0.012)	(0.013)	(0.014)
Observations	198,602,271	198,700,740	198,964,006	200,500,560
Adj R-squared	0.274	0.274	0.274	0.274
Fixed Effects	G, T, W	G, T, W	G, T, W	G, T, W
Panel B: State × Time Fixed Effects				
After × Treated	-0.026**	-0.031***	-0.036***	-0.038***
	(0.012)	(0.010)	(0.010)	(0.010)
Observations	198,602,271	198,700,740	198,964,006	200,500,560
Adj R-squared	0.311	0.311	0.311	0.311
Fixed Effects	G, S×T, W	G, S×T , W	G, S×T , W	G, S×T , W
Panel C: Date Fixed Effects				
After × Treated	-0.024*	-0.030**	-0.045***	-0.065***
	(0.013)	(0.012)	(0.013)	(0.014)
Observations	198,602,269	198,700,738	198,964,004	200,500,558
Adj R-squared	0.357	0.357	0.357	0.357
Fixed Effects	G, D, W	G, D, W	G, D, W	G, D, W

Table 11. Subsample Analyses based on Perceived and Actual Local Pollution Levels

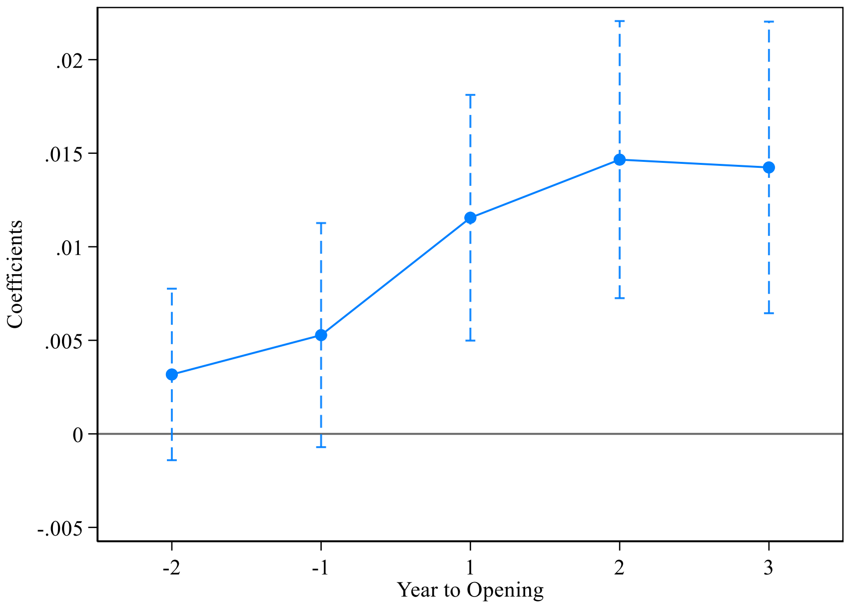
This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. The explanatory variable of interest is After × Dist. < 5km. The sample is restricted to sales of residential properties within 10 kilometers of a monitoring station that occurred 3 years before or after the station's establishment. Column 1 restricts the sample to areas with *perceived* low pollution and *actual* low pollution levels; Column 2 restricts the sample to areas with *perceived* high pollution and *actual* high pollution levels; Column 3 restricts the sample to areas with *perceived* low pollution and *actual* high pollution levels; Column 4 restricts the sample to areas with *perceived* high pollution and *actual* low pollution levels. Areas are classified as *perceived* low (high) pollution areas if the number of TRI industrial facilities surrounding the monitoring station one year before its opening is below (above) the sample median; areas are classified as *actual* low (high) pollution areas if the daily PM 2.5 values obtained from the monitoring station averaged across the first year of its opening is below (above) the sample median. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) Perceived Low Actual Low	(2) Perceived High Actual High	(3) Perceived Low Actual High	(4) Perceived High Actual Low
After × Dist. < 5km	0.008	0.015***	0.003	0.014***
	(0.005)	(0.005)	(0.006)	(0.004)
Observations	560,922	1,256,051	336,592	1,048,244
Adj R-squared	0.825	0.813	0.823	0.808
Neighborhood FE	Z	Z	Z	Z
Time FE	M × YM	M × YM	M × YM	M × YM
Prop. & Trans. Controls	Y	Y	Y	Y
Distance Bin FE	Y	Y	Y	Y

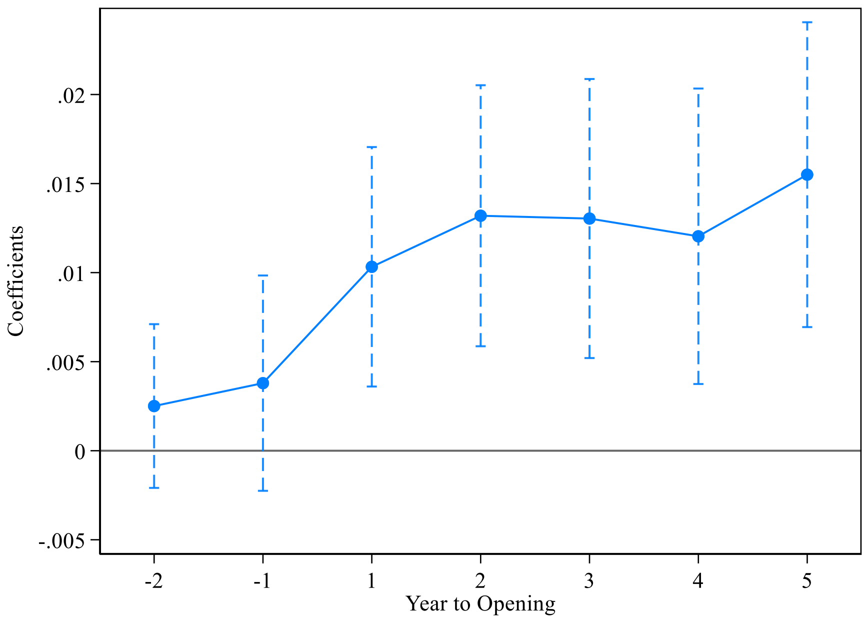
Appendix Figure 1. Dynamic Effect using an Extended Sample Period

This figure shows coefficient estimates of price effects from the regression of log transaction prices on $\mathbb{1}[\text{Distance}_i < 5\text{km}]$ interacted with a set of time period dummies that indicate the number of years before and after the establishment of a monitoring station. The sample is restricted to transactions of properties within 10 kilometers of a monitoring station, occurring within 3 years before or 3 years (Panel A) and 5 years (Panel B) after the station's establishment. The regression includes all property and transaction controls, zip code fixed effects and monitoring station × Sale Year-Month fixed effects. Year −3 is the omitted reference period while Year 1 is the first year in which the monitoring station opened. Ninety-five percent confidence intervals are displayed around each point estimate. Standard errors are clustered at the zip code level.

Panel A. Dynamic Effect by Number of Years

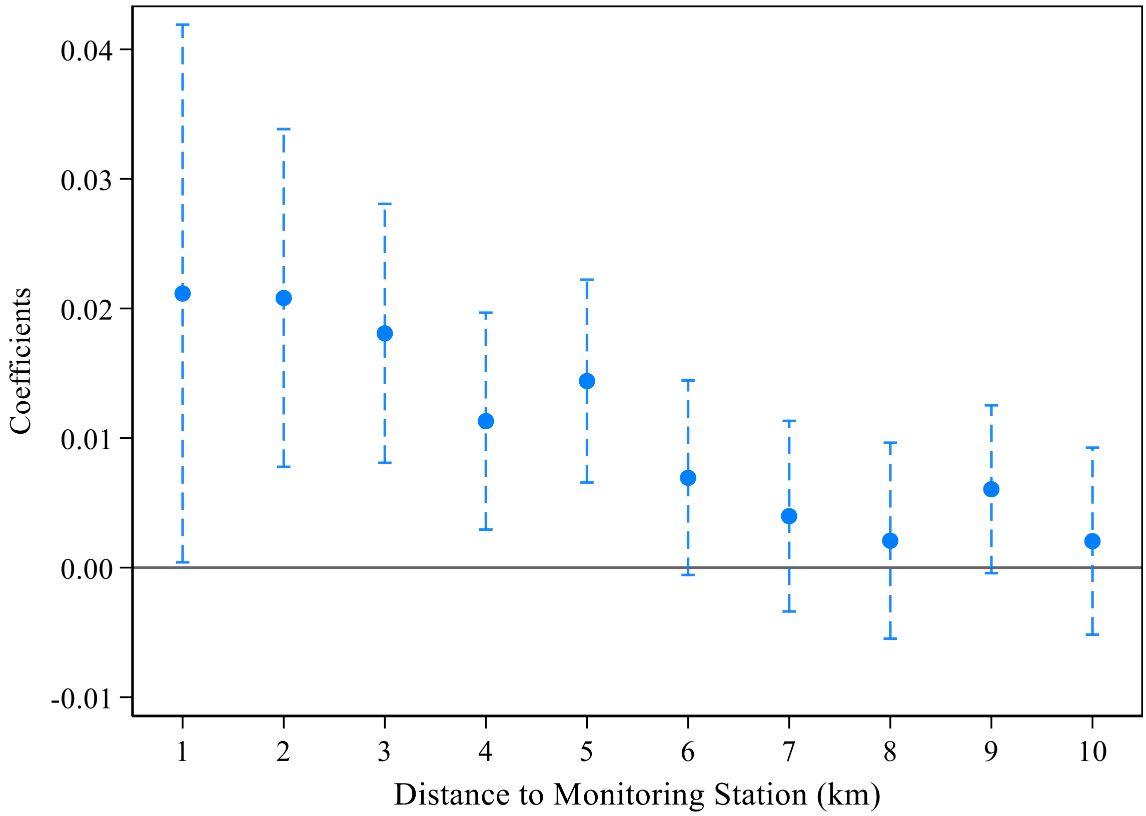


Panel B. Dynamic Effect by Number of Years using an Extended Sample Period



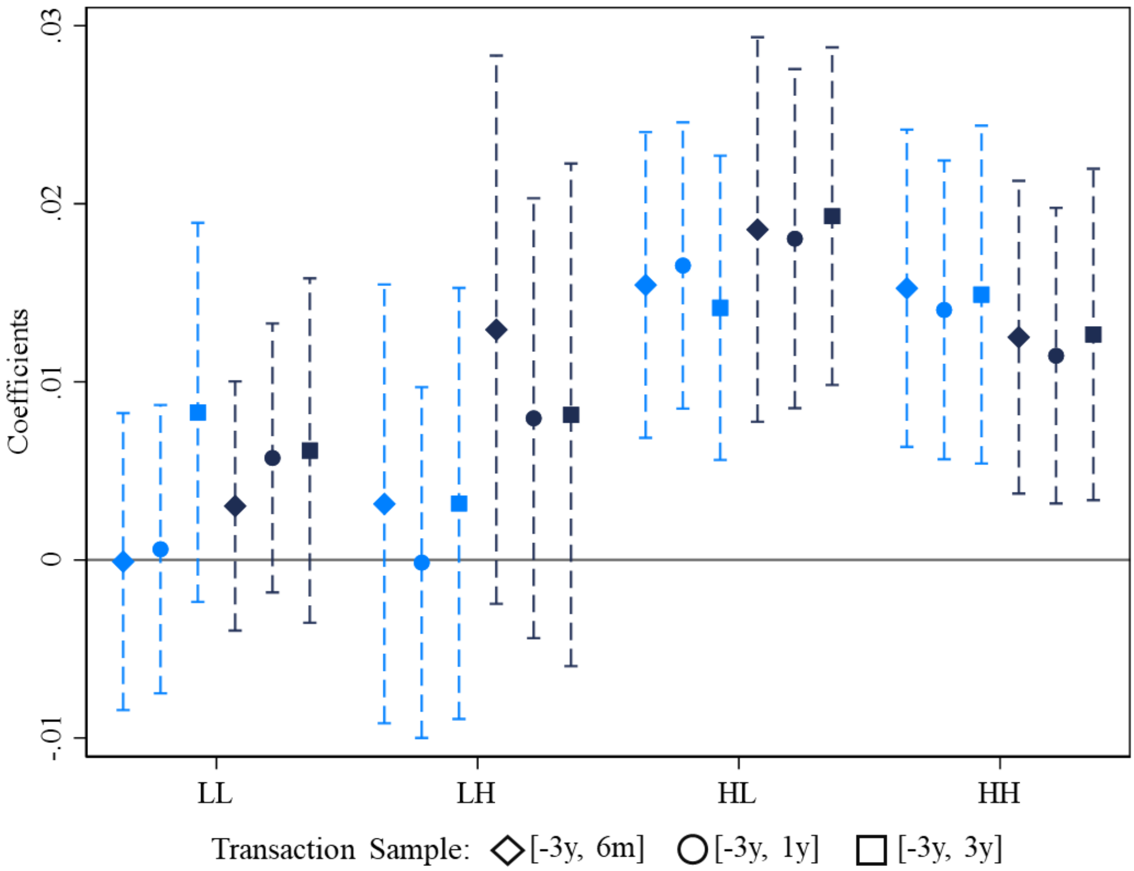
Appendix Figure 2. Distance Decay Effects of Monitoring Station on Housing Prices

This figure presents the effects of monitoring station on housing prices. Each line represents a point estimate and a 95% confidence interval from a regression of log transaction prices on the interaction between an indicator for transactions occurring after the station's establishment and an indicator for houses located within various distance intervals, ranging from 0-1 kilometer to 9-10 kilometers of a monitoring station. The sample consists of two groups: comparison group, including properties within 10-20 kilometers of a monitoring station, and the corresponding treatment group. Both groups include transactions that occurred within 3 years before or after the station's establishment. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. Standard errors are clustered at the zip code level.



Appendix Figure 3. Robustness—Subsample Analyses based on Perceived and Actual Local Pollution Levels

This figure presents the coefficient estimates of price effects from the regression of log transaction prices on $\mathbb{1}[\text{Distance}_i < 5\text{km}]$. Each line represents a point estimate and a 95% confidence interval from a regression of log transaction prices using a sample restricted to sales of residential properties within 10 kilometers of a monitoring station that occurred 3 years before and 6 months after, 3 years before and 1 year after, or 3 years before and 12 months after the station's establishment. Regressions in LL restrict the sample to areas with *perceived* low pollution and *actual* low pollution levels; regressions in HH restrict the sample to areas with *perceived* high pollution and *actual* high pollution levels; regressions in LH restrict the sample to areas with *perceived* low pollution and *actual* high pollution levels; regressions in HL restrict the sample to areas with *perceived* high pollution and *actual* low pollution levels. Areas are classified as *actual* low (high) pollution areas if the daily PM 2.5 values obtained from the monitoring station averaged across the first year of its opening is below (above) the sample median. Areas are classified as *perceived* low (high) pollution areas if the number of TRI industrial facilities (in light blue) or the total amount of air emissions released by these TRI industrial facilities (in navy blue) surrounding the monitoring station one year before its opening is below (above) the sample median The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. The standard errors are clustered at the zip code level.



Appendix Table 1. Robustness to County-level Shocks

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. All columns use a sample of residential property sales within 10 kilometers of a monitoring station occurring 3 years before or after the station's establishment. Column 1 narrows the sample to properties situated in counties designated as *attainment* status by the EPA, while Column 2 narrows the sample to properties located in counties designated as *nonattainment* status by the EPA. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
After × Dist. < 5km	0.010**	0.010***	
	(0.004)	(0.004)	
After × Dist. < 5km × $\mathbb{1}$[Attainment]			0.014***
			(0.004)
After × Dist. < 5km × $\mathbb{1}$[Nonattainment]			0.008*
			(0.004)
Observations	1,649,739	2,172,527	3,822,505
Adj R-squared	0.786	0.836	0.816
Neighborhood FE	Z	Z	Z
Time FE	M × YM	M × YM	M × YM
Prop. & Trans. Controls	Y	Y	Y
Distance Bin FE	Y	Y	Y
Sample	Attainment Only	Nonattainment Only	Full Sample

Appendix Table 2. Heterogeneity of Price Effects by Zip Code Characteristics

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. In Columns 1 and 2, $\mathbb{1}$[< Median] is an indicator for properties situated in zip codes with below median household income or per capita income, respectively, based on the 2015 ACS 5-year estimates. Similarly, $\mathbb{1}$[> Median] is an indicator for properties in zip codes with above median household income or per capita income. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. All columns use a sample of residential property sales within 10 kilometers of a monitoring station occurring 3 years before or after the station's establishment. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) Household Income	(2) Per Capita Income
After × Dist. < 5km × $\mathbb{1}$[< Median]	0.011**	0.012***
	(0.005)	(0.005)
After × Dist. < 5km × $\mathbb{1}$[> Median]	0.009**	0.009**
	(0.004)	(0.004)
Observations	3,750,290	3,755,390
Adj R-squared	0.816	0.817
Neighborhood FE	Z	Z
Time FE	M × YM	M × YM
Prop. & Trans. Controls	Y	Y
Distance Bin FE	Y	Y

Appendix Table 3. Effects of Monitoring Station Establishment on Neighborhood-level Emissions

This table presents ordinary least squares estimates where the dependent variables are the natural log of one plus the total number of TRI Facilities (Column 1), total amount of toxic release (Column 2), total amount of air release (Column 3), total amount of water release (Column 4), and total amount of land release (Column 5) in the area surrounding monitoring station. $After$ is an indicator for observations after the establishment of a monitoring station and $Dist. < 5km$ is an indicator for areas located within 5 kilometers of a monitoring station. The sample is restricted to observations of areas within 10 kilometers of a monitoring station occurring 3 years before or after the station's establishment. All regressions include $Dist. < 5km$ and monitoring station (M) × Year (Y) fixed effects. The standard errors are clustered at the monitoring station level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) No. of Facilities	(2) Total Release	(3) Air Release	(4) Water Release	(5) Land Release
After × Dist. < 5km	-0.026**	-0.361***	-0.342***	0.021	-0.190
	(0.012)	(0.100)	(0.096)	(0.082)	(0.120)
Observations	10,574	10,574	10,574	10,574	10,574
Adj R-squared	0.700	0.450	0.469	0.303	0.092
Fixed Effects	M × Y	M × Y	M × Y	M × Y	M × Y

Appendix Table 4. Price effects of Establishment of Non-Regulatory Monitoring Stations

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. The explanatory variable of interest is After × Dist. < 5km, which takes the value of one for a property within 5 kilometers of a non-regulatory monitoring station and transacted after the station's establishment. The sample is restricted to sales of residential properties within 10 kilometers of a non-regulatory monitoring station that occurred 3 years before or after the station's establishment. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. Columns 1 to 6 correspond to their counterparts in Columns 1,4,6 to 9 of Table 2, respectively, which explore three geographical levels: zip code (Z), monitoring station (M), and county (C). The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
After × Dist. < 5km	-0.001	-0.000	-0.006	-0.002	-0.001	-0.000
	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.004)
Observations	837,382	831,769	833,898	797,820	837,250	831,789
Adj R-squared	0.872	0.882	0.877	0.894	0.872	0.882
Neighborhood FE	Z	Z	M	M	Z, M	Z, M
Time FE	M × YM	M × YM × PT × R × I	Z × YM	Z × YM × PT × R × I	M, C × YM	C × YM × PT × R × I
Prop. & Trans. Controls	Y	Y	Y	Y	Y	Y
Distance Bin FE	Y	Y	Y	Y	Y	Y

Appendix Table 5. Subsample Analyses based on Perceived and Actual Local Pollution Levels – Non-regulatory Monitoring Stations

This table presents ordinary least squares estimates where the dependent variable is the natural logarithm of the transaction price. The explanatory variable of interest is After × Dist. < 5km. The sample is restricted to sales of residential properties within 10 kilometers of a non-regulatory monitoring station that occurred 3 years before or after the station's establishment. Column 1 restricts the sample to areas with *perceived* low pollution and *actual* low pollution levels; Column 2 restricts the sample to areas with *perceived* high pollution and *actual* high pollution levels; Column 3 restricts the sample to areas with *perceived* low pollution and *actual* high pollution levels; Column 4 restricts the sample to areas with *perceived* high pollution and *actual* low pollution levels. Areas are classified as *perceived* low (high) pollution areas if the number of TRI industrial facilities surrounding the monitoring station one year before its opening is below (above) the sample median; areas are classified as *actual* low (high) pollution areas if the daily PM 2.5 values obtained from the monitoring station averaged across the first year of its opening is below (above) the sample median. Property controls consist of indicators for number of bedrooms and bathrooms, property age percentiles, building square footage percentiles, land square footage percentiles, mobile home, pool, and property type (PT). Transaction controls include indicators for corporate buyer, cash purchase, resale (R), purchase for investment purpose (I). Distance Bin FE represents fixed effects for distance from the transacted property to a monitoring station, with 100 distance bins, each covering a 0.1-kilometer range. The regressions include all property and transaction controls, zip code (Z) fixed effects and monitoring station (M) × Sale Year-Month (YM) fixed effects. The standard errors are clustered at the zip code level and presented below the coefficient in parenthesis. *, **, *** represent significance at the 10%, 5%, and 1% level, respectively.

	(1) Perceived Low Actual Low	(2) Perceived High Actual High	(3) Perceived Low Actual High	(4) Perceived High Actual Low
After × Dist. < 5km	0.010	0.006	-0.020	-0.007
	(0.013)	(0.009)	(0.017)	(0.008)
Observations	41,625	232,486	38,833	159,007
Adj R-squared	0.857	0.898	0.754	0.822
Neighborhood FE	Z	Z	Z	Z
Time FE	M × YM	M × YM	M × YM	M × YM
Prop. & Trans. Controls	Y	Y	Y	Y
Distance Bin FE	Y	Y	Y	Y