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Does emissions data disclosure of Waste-to-Energy incineration plants mitigate NIMBYism concerns? Evidence from the housing market

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Abstract

This study examines the impact of emissions data disclosure on alleviating NIMBY-ism (Not In My Backyard) concerns surrounding Waste-to-Energy (WtE) incineration plants. Leveraging China's 2017 "Installing, Erecting, and Networking" (IEN) policy as a quasi-natural experiment, we employ a difference-in-differences (DID) approach to analyze over 35,000 housing transactions near 13 plants. Results indicate that the IEN policy attenuates the housing price gradient by 30.43%, equivalent to 38% of an urban Chinese resident's annual disposable income. This robust evidence highlights how transparency policies can enhance public trust and thus promote more sustainable urban development.

JEL classifications: Q28, Q58, R31

Keywords: information disclosure, incineration, NIMBYism concerns, housing price gradient

1 Introduction

Globally, rapid urbanisation and increasing waste generation have presented significant challenges in managing municipal solid waste (MSW). According to the World Bank (Kaza et al., 2018), global waste generation is projected to rise from 2.01 billion tonnes in 2016 to 3.40 billion tonnes by 2050, with the most significant increases expected in developing countries across Asia and Africa. In response to this challenge, Waste-to-Energy (WtE) incineration has gained global attention as a sustainable solution for addressing the growing challenge of MSW management (Fontaine and Rocher, 2024; Hultman and Corvellec, 2012). Countries like Denmark, Sweden, and Japan have integrated WtE into their waste management systems, reducing landfill use by up to 70% while also reducing greenhouse gas emissions (Malinauskaite et al., 2017). However, despite these environmental benefits, WtE incineration plants frequently encounter public opposition, commonly framed as the Not In My Backyard (NIMBY) effect (Gamson and Modigliani, 1989; Gamalerio and Negri, 2023). The NIMBY effect oftentimes compels local governments to delay or cancel important waste management projects, significantly impeding MSW treatment and threatening social stability (Mak, 2020; Büchler and v. Ehrlich, 2023). To address these concerns, many countries have begun implementing information disclosure policies regarding WtE incineration plants, aiming to alleviate NIMBYism concerns. Guidelines from the United Nations Environment Programme (UNEP) also suggest that transparency is critical for promoting public trust and improving social acceptance of waste management projects (United Nations Environment Programme, 2020).

Despite the well-intentioned nature of these information disclosure policies, their effectiveness in altering public perceptions and mitigating NIMBYism concerns remains uncertain. This study addresses this gap by investigating the causal effect of real-time emissions data disclosure on public perception and housing market outcomes. We utilize China's 2017 "Installing, Erecting, and Networking" (IEN) policy as a quasi-natural experiment. This policy mandates the real-time disclosure of emissions data at the entrances of WtE incineration plants, aiming to enhance transparency and reduce public fears about pollution from waste incineration. Applying a difference-in-differences (DID) approach to a dataset comprising over 35,000 housing transactions across 13 cities, we examine the direct effect of emissions data disclosure on property prices.

Our study offers a three-fold contribution. First, to the best of our knowledge, this is the first study to examine the causal effect of real-time emissions data disclosure on public perception and housing markets.

We provide robust empirical evidence through our DID analysis that real-time information disclosure plays a significant role in attenuating the housing price gradient. Second, this study quantifies the attenuation of the housing price gradient by 30.43%, which is equivalent to a substantial reduction of 38% of an urban Chinese resident's annual disposable income. This finding underscores significant economic implications for public policy and real estate markets, suggesting that enhanced transparency in emissions data offers tangible benefits in mitigating economic losses associated with perceived environmental risks. Third, our results show that transparency through data disclosure can effectively mitigate NIMBYism concerns, thereby enhancing public trust in WtE incineration plants. From a policy-making standpoint, these findings highlight broader implications for policymakers seeking to balance the environmental and social dimensions of WtE incineration, offering a pathway towards more sustainable urban development by fostering public acceptance of environmental infrastructure through data-driven transparency.

Our study is primarily related to three strands of literature. First, our study is related to the broad literature on environmental amenity valuation. Following Ridker and Henning (1967), who were the first to incorporate environmental amenities into the study of residential property values, a substantial body of literature has emerged to investigate how environmental amenities are capitalized into property values, such as air quality (Amini et al., 2022; Hitaj et al., 2018; Huang and Lanz, 2018; Pinchbeck et al., 2023; Smith and Huang, 1995), water quality (Bin et al., 2017; Kuwayama et al., 2022; Leggett and Bockstael, 2000), and undesirable land usage (Bauer et al., 2017; Tanaka and Zabel, 2018; Davis, 2011). As incineration technology has been developed, there has been increasing focus on the hedonic estimation of externalities associated with incineration plants, with studies showing that proximity to these plants tends to reduce housing values (Kiel and McClain, 1995; Song et al., 2023). Rivas Casado et al. (2017) estimate the impacts of three incineration plants in England and find that the impacts range from approximately 0.4% to 1.3% of the mean housing prices in affected areas. Our study contributes to this body of literature by showing that prior to the implementation of information disclosure, housing prices near 13 WtE incineration plants in China suffer devaluation. Specifically, for every additional km away from the plants, housing prices on average increase by 1.38%.

Second, our study adds to the growing research area that investigates the impact of environmental law enforcement on housing prices. Previous studies have shown that environmental regulations could lead to an increase in housing prices or rental prices due to a reduction in pollution concentration (Greenstone and Gallagher, 2008; Lang, 2015; Walsh et al., 2011; Fan et al., 2024). For example, Chay and Greenstone (2005) find that a 1 μg/m^3 reduction in total suspended particulates (TSPs) induced by the Clean Air Act Amendments (CAAA) results in a 0.2–0.4 percent increase in mean housing prices. Grainger (2012) find that the 1990 CAAA leads to a significant increase in rents, while the estimated percentage effect is half as large as that of owner-occupied housing values. Similarly, Bento et al. (2015) find that households in the lowest quintile of the income distribution receive annual benefits from the 1990 CAAA equal to 0.30% of their income on average, over twice as much as those in the highest quintile. By contrast, Agarwal et al. (2019) find that the NOx Budget Trading Program (NBP), which is a cap-and-trade system, works as a double-edged sword for housing markets. In areas with low manufacturing intensity, housing prices increase, whereas in areas with high manufacturing intensity, housing markets are weakened. Despite this growing literature, the impact of real-time environmental information disclosure on housing prices, another form of environmental regulation, remains underexplored. Our study provides new insights into this issue by examining the impact of China's 2017 IEN policy, which aims to achieve real-time information disclosure for WtE incineration plants.

Third, more closely related to our study are those contributions investigating housing market responses to direct disclosure of environmental information. Bui and Mayer (2003) find no statistically significant relationship between changes in toxic releases and house prices, suggesting that the reported toxic releases might have been considered of low quality and thus ignored by homebuyers. Mastromonaco (2015) finds that listing an existing firm in the TRI leads to a decrease in housing prices of up to 11% within one-and-a-half kilometers. Moulton et al. (2024) demonstrate that news coverage of the new TRI data leads to a significant 8–11% drop in housing prices within 0.5 miles of the largest polluters. Marcus and Mueller (2024) find that housing prices decrease by about 31 to 42 percent in Paulsboro after the release of information about per- and polyfluoroalkyl substances (PFAS) contamination in local drinking water supplies. However, these studies largely focus on the adverse impacts of disclosing negative environmental information, less is known about the potential benefits of real-time emissions information disclosure, which may offer more immediate reassurance to the public. Through our analysis of the impact of the real-time emissions data disclosure on the housing price gradient, we provide evidence that transparency through real-time emissions data disclosure significantly reduces residents' perceived levels of risks and mitigates NIMBYism concerns. This is crucial for understanding the potential benefits associated with actions to increase transparency in emissions data.

The remainder of the paper is organized as follows: Section 2 provides background information on the 2017 IEN policy. Section 3 introduces data and measures. Section 4 specifies the empirical strategy. Section 5 reports and discusses the results. Section 6 provides concluding remarks.

2 Institutional background

In recent years, NIMBY incidents related to WtE incineration plants have become increasingly frequent, underscoring that public concerns regarding the transparency and accountability of these facilities have reached unprecedented levels. To effectively alleviate the fears of the public and mitigate the NIMBY effect, the government has been aware of the urgency and necessity of implementing information disclosure policies of WtE incineration plants. Accordingly, on April 20, 2017, the Ministry of Ecology and Environment (MEE) of the People's Republic of China issued a regulation named *Notice on Matters Relating to the Installation of Automatic Pollutant Emission Monitoring Equipment and Networking in Domestic WtE Incineration Plants*. This regulation mandated all WtE incineration plants to fully complete the three tasks of IEN by September 30, 2017. "Installing" is to require all plants to install automatic pollution source monitoring equipment in accordance with the law, and monitor emissions information in real time; "Erecting" is to set up display screens at plant entrances or prominent locations for the public to view, and to make the monitored data available to the public in real time; "Networking" is to require the plants' automatic monitoring systems to be networked with the environmental protection departments, thereby facilitating the supervision of the environmental protection departments.

As a result, by August 2017, 176 out of 246 established plants in the country, excluding plants that have been shut down, about to be shut down and were within six months of technological transformation, have completed the IEN tasks, with a completion rate of 74.58%. Among them, plants in Beijing, Tianjin, Heilongjiang, Shanghai, Fujian, Guizhou and other provinces (autonomous regions and municipalities) and the Xinjiang Production and Construction Corps have all completed the tasks. In Anhui, Shandong, Jiangsu, and Sichuan, the work progress was relatively fast, with completion rates of 91.67%, 90.91%, 84.85%, and 80%, respectively. In contrast, in Shanxi, Liaoning, Jilin, Henan and other provinces, the work progress lagged significantly behind, with completion rates of less than 20%.

Regarding the plants with slow progress, the MEE issued a new regulation, requiring all provincial environmental protection departments to schedule the plants yet to complete the tasks, list the timetables for the eventual completion of the tasks, and report these to the MEE. Plants failing to complete the tasks by the deadline would face strict legal consequences. According to *Law of the People's Republic of China on the Prevention and Control of Atmospheric Pollution*, these plants will be penalized at the highest level and issued with a notice of order to make corrections; and from October 1, 2017, they will be subjected to consecutive daily penalties. According to the data released by the MEE in February 2018, by the end of 2017, all 278 plants nationwide have completed the tasks. Furthermore, the MEE stipulated that newly commissioned plants should also be included in the scope of IEN to achieve full regulatory coverage.

Thus, this policy context provides an ideal setting for this study. Using the staggered completion of the tasks of different WtE incineration plants at different time points as a quasi-natural experiment, we could investigate the impact of the IEN policy on property values, thus examining the effectiveness of transparency measures in alleviating NIMBYism concerns.

3 Data

3.1 WtE incineration plant data

We obtain administrative data on all WtE incineration plants in China from the Open Platform for Automatic Monitoring Data of Domestic WtE Incineration Plants.[1] The data contain detailed information on a variety of plant characteristics, including the address, the designed treatment capacity, and the commissioning date of each furnace. Using this data, we are able to identify plants that were put into operation before the policy was issued, as well as investigating the effect heterogeneity among different plants later in Section 5.6. It is worth noting that some of the cities in our dataset of resale apartments only start to have transaction records in the second half of 2016. To ensure an adequate amount of ex-ante data, we only collect a list of WtE plants from cities that start to have transaction records in or prior to the second half of 2016.[2] This results in a total of 95 plants being included in our analysis. We further exclude WtE plants that came into operation after the regulation was issued, reducing our sample to 42 plants.

3.2 Housing transaction data

Our housing transaction data come from a dataset of resale apartments provided by Beike, which is the largest trading platform for second-hand residential properties in China.[3] The micro-data on individual level

[1]The MEE mandates that starting from January 2, 2020, the daily average values of five key pollutants, along with furnace temperature data from all WtE incineration plants, must be publicly disclosed on a daily basis on this platform at https://ljgk.envsc.cn.

[2]The resale apartment dataset contains transaction data from 25 cities in China, and 13 of these cities start to have transaction data in or prior to July 2016. These 13 cities are Beijing, Shanghai, Shenzhen, Dalian, Hangzhou, Jinan, Langfang, Nanjing, Qingdao, Suzhou, Tianjin, Changsha, and Wuhan.

[3]Website: https://www.ke.com.

from this dataset is superior to other city-level or provincial-level housing transaction data, for it captures detailed information about individual transactions, including specific property characteristics, transaction prices, and buyer-seller dynamics (Chu et al., 2021; Mei et al., 2021).

We start by determining the time horizon of the sample. The MEE approved *Management Regulations on the Application of Automatic Monitoring Data of Domestic WtE incineration Plants* on October 11, 2019, calling for the implementation of the regulations from January 1, 2020. In order to avoid any potential noise caused by this external shock, we limit analysis to the period before January 2020. Moreover, given that most cities in our dataset have only had substantial housing data since 2016, we set the starting point of our data to January 2016.[4] Next, we collect the distribution of neighborhoods within 10 km of treated plants through Baidu Map[5] and preliminarily exclude the plants with scarce sample data.[6] We further gather the names of the communities surrounding the plants and match them with those in the dataset that belong to the same districts and streets. This matching process enables us to identify the accurate communities and further exclude plants with scarce sample data. Finally, we obtain 35,292 transaction data within 10 km of 13 WtE plants, which cover 7 cities and 27 administrative districts in China. The data record each apartment's unit transaction price per m^2, whose logarithm acts as the dependent variable in our model.

To reduce the influence of outliers, we trim the top and bottom 1% of the data using the transaction price per m^2 and floor area. Each transaction record contains detailed characteristics of the apartment, including number of rooms, floor number, year of construction, and decoration degree. The data also contains information about the specific street and district of each community, allowing us to gather the distance between each community and the nearest amenities by Baidu map, such as subway stations and tertiary hospitals. Considering that the better amenities around the governments can increase the attractiveness of the surrounding properties and thus the property prices, the distances from the communities to their nearest district and municipal governments are also calculated given their latitude and longitude coordinates.

To control for neighborhood differences between properties, we supplement this housing transaction data with demographic characteristics at the district level, including population, population density, household size, illiteracy rate, and the number of criminal cases. The first four variables are obtained from the Bureau

[4]Beijing Beikong Green Sea Energy Environmental Protection Co., Ltd., Shanghai Dongshitang WtE Co., Ltd., and Shanghai Tianma WtE Co., Ltd. were put into operation after January 2016. For these plants, we apply the housing transaction data after they were in operation.

[5]Website: https://map.baidu.com.

[6]In order to minimize opposition from residents, most WtE incineration plants in China are built far away from densely populated areas. Thus, it is challenging to obtain adequate housing data for most plants.

of Statistics and census statistical yearbooks from various cities, and the last variable is obtained from China Judgements Online.[7]

3.3 Completion time of IEN

In Supplementary Appendix Table A1, we report the completion dates of IEN regarding each WtE incineration plant, which are collected from the MEE in the corresponding cities. It can be seen that in some cases, the completion time of IEN is indeed later than September 30, 2017. For example, the completion time for Everbright Environmental Energy Suzhou Co., Ltd. is December 31, 2017. Therefore, we use the actual completion time of each plant instead of September 30, 2017 as the treatment dates in our DID analysis.

3.4 Summary Statistics

A brief description and summary statistics for the variables can be found in Table 1. The average apartment is 79.29 m^2 (853.47 ft^2) in size and has 2.1 bedrooms. The average straight-line distances to the plant, district government, and municipal government are 6.431 km, 5.825 km, and 12.336 km, respectively. 60.6% of the apartments are within 1 km of the nearest subway station. 9.8% of the apartments are roughcast and 35.7% of the apartments are simply decorated. Finally, 85.3% of the apartments were sold after the completion of "Installing, Erecting, and Networking" (hereafter, CIEN).

4 Empirical strategy

4.1 Baseline specification

The main objective of this study is to capture the impact of IEN on the housing market after controlling for potential confounders and other drivers of property prices. To this end, a hedonic model in a DID framework is conducted. One identification issue is whether IEN is exogenous to the housing market. According to government documents, the MEE's primary motivation for launching IEN was to strengthen environmental regulation and promote the healthy development of the incineration industry, rather than to bring direct economic impacts to the housing market. Thus, we expect the implementation of IEN is independent on housing prices (Amini et al., 2022; Mastromonaco, 2015). Our DID specification is similar to that of Archibong and Annan (2017), who perform a DID estimation on cross-sectional data with some observations entering the sample before the treatment and others after the treatment. Let Price_{ijt} be the average price per m^2 of

[7] Website: https://wenshu.court.gov.cn.

Table 1: Variables in the models and their descriptive statistics

Category	Variable	Description	Mean	Standard deviation	Minimum	Maximum
Dependent variable	lnPrice	Property transaction price per unit area (logarithm)	10.500	0.535	9.183	11.591
Housing characteristics	Room	Number of bedrooms	2.074	0.770	1	5
	Area	Floor area	79.292	30.61	30	198
	Age_impute	Years of construction (0-5 years=1, 6-10 years=2, 11-15 years=3, 16-20 years=4, 21-30 years=5, over 30 years=6)	3.113	1.066	1	6
	Age_missing	Dummy variable for whether the age is missing (yes=1, no=0)	0.004	0.060	0	1
	Roughcast	Dummy variable for whether the decoration degree is roughcast (yes=1, no=0)	0.098	0.298	0	1
	Simple decoration	Dummy variable for whether the decoration degree is simple decoration (yes=1, no=0)	0.357	0.479	0	1
	Floor	Floor of apartment (low-rise=1, middle-rise=2, high-rise=3)	2.150	0.807	1	3
	Subway	Dummy variable for whether the nearest subway station is within 1 km of the community (yes=1, no=0)	0.606	0.489	0	1
	Bungalow	Dummy variable for whether the build type is bungalow (yes=1, no=0)	0.001	0.038	0	1
	Tower	Dummy variable for whether the build type is tower-type (yes=1, no=0)	0.086	0.281	0	1
	Tower_slab	Dummy variable for whether the build type is tower-type combined with slab-type (yes=1, no=0)	0.050	0.218	0	1
	Dis_district	Straight-line distance from the community to the nearest district government	5.825	5.802	0.128	32.8
	Dis_municipal	Straight-line distance from the community to the municipal government	12.336	10.099	0.275	61.8
	Hospital	Dummy variable for whether the nearest tertiary hospital is within 5.7 km of the community (yes=1, no=0)[a]	0.707	0.455	0	1
	Dis_inciner	Straight-line distance from the community to the incineration plant	6.431	2.344	0.443	10.000
District characteristics	Household size	Number of people in the household	2.555	0.159	2.1	3.14
	Illiteracy rate	Proportion of illiterate population to the population aged 15 and above	2.794	1.192	0.82	6.35
	lnPopulation	Permanent population (logarithm)	5.141	0.884	3.472	6.322
	lnDensity	Population per square km (logarithm)	8.603	1.049	5.403	10.372
	lnCrime	Number of criminal cases (logarithm)	7.400	0.727	4.868	8.394
Post		Dummy variable for whether the transaction occurs after CIEN (yes=1, no=0)	0.853	0.354	0	1

Notes: This table presents descriptive statistics of dependent variables (top panel), housing characteristics (middle panel), district characteristics (middle panel), and treatment variable (bottom panel) for the sample of apartment-type property transactions. Transaction price and housing area are winsorized at the 1st and 99th percentiles.

[a] To better capture the distribution of the sample, we use the average of the distances from all observations to the nearest tertiary hospital to construct the *Hospital* variable.

apartment i in district j sold at time t. We specify the estimated DID regression as follows, in which one difference is before and after CIEN and the other is the price difference between apartments at different distances to the same plant:

$$\begin{aligned}\ln \text{Price}_{ijt} = &\beta_0 + \beta_1 \text{Dis\_inciner}_{ist} + \beta_2 \text{Post}_{st} + \beta_3 \text{Dis\_inciner}_{ist} \times \text{Post}_{st} \\ &+ \beta_4 H_i + \delta_k + \gamma_t + \theta_{ct} + \epsilon_{ijt} \end{aligned} \tag{1}$$

where $\ln \text{Price}_{ijt}$ is the natural log of the average price per m^2 of apartment i in district j at time t. $\text{Dis\_inciner}_{\text{ist}}$ is the distance from apartment i to plant s at time t. Post_{st} is an indicator for the completion of the IEN policy for plant s at time t. The interaction term $\text{Dis\_inciner}_{\text{ist}} \times \text{Post}_{\text{st}}$ represents the interaction between $\text{Dis\_inciner}_{\text{ist}}$ and Post_{st}. H_i is a vector of hedonic variables accounting for property characteristics. We also include the business-district fixed effects, δ_k, to capture time-invariant determinants of housing prices in a business district.[8] To control for time-varying factors, we include a set of time fixed effects γ_t. Year fixed effects account for general trends in housing prices. Quarter fixed effects account for seasonal trends. Month fixed effects capture monthly patterns in the housing market. The quarter-by-year fixed effects allow the seasonality effects to vary from year to year. The month-by-year fixed effects allow the monthly patterns to vary from year to year. Moreover, following Hu and Lee (2020), we denote θ_{ct} as the city-year-month or city-year-quarter fixed effects, where θ_{ct}s are the coefficients of a set of dummy variables for each city in a given month (or quarter) during the sample period that capture the general time pattern of the primary outcome in the same city. To deal with the possibility of autocorrelation in the residuals, we cluster the error term ε_{ijt} by community and month as suggested in Bertrand et al. (2004).

The coefficients of $\text{Dis\_inciner}_{\text{ist}}$ and $\text{Dis\_inciner}_{\text{ist}} \times \text{Post}_{\text{st}}$ are our major interests. β_1 represents the housing price gradient at different distances from the plants before CIEN (i.e., Post_{st}=0), which is expected to be positive: ceteris paribus, for each kilometer away from the plants, the average property price increases by $100\beta_1\%$. However, after CIEN, the gradient becomes $\beta_1 + \beta_3$: ceteris paribus, for each kilometer away from the plants, the average housing price increases by $100(\beta_1 + \beta_3)\%$. Therefore, β_3 identifies the impact of CIEN on the gradient. A negative β_3 implies that CIEN narrows the housing price gap between the apartments proximate to and distant from the plants.

[8] In China, business districts are at a smaller geographical scale than districts, and play a crucial role in shaping the housing market map (He et al., 2019; Qin and Han, 2013). Therefore, we control for business-district fixed effects instead of district fixed effects to control for confounding factors at a more localized geographical level.

4.2 Location heterogeneity effect

The above specification assumes that the housing price gradient is constant over all distances to the plant. However, the relationship between housing prices and distance to the plant is not linear (Hite et al., 2001). Housing prices rise gradually with increasing distance, but as the distance increases, the prices could rise more slowly. To capture the location heterogeneity effect, the continuous variable $\text{Dis\_inciner}_{\text{ist}}$ in Eq. 1 is replaced with indicators that an apartment is located within 0-2 km, 2-4 km, 4-6 km, 6-8 km, or 8-10 km of the plant[9] and the following specification is estimated. The first four segments form part of the impact area, whereas the fifth segment acts as a natural control group.

$$\ln \text{Price}_{ijt} = \beta_0 + \beta_1 \text{Post}_{st} + \sum_{p=1}^{5} \gamma_p \text{Ring}_p + \sum_{p=1}^{5} \phi_p (\text{Post}_{st} \times \text{Ring}_p) + \beta_2 H_i + \delta_k + \gamma_t + \theta_{ct} + \epsilon_{ijt} \tag{2}$$

where Ring_p $(p = 1, 2, 3, 4, 5)$ represent distance rings of 0-2 km, 2-4 km, 4-6 km, 6-8 km and 8-10 km, respectively. The interaction terms are used to investigate whether the effect of CIEN varies among the five rings and Ring_5 acts as the reference category, thus ϕ_1 through ϕ_4 are the parameters of interest.

4.3 Parallel trends test

In order to test for the parallel trends assumption and to identify if the treatment effect changes over time, we conduct an event study exercise following Jacobson et al. (1993) and Autor (2003). The regression model is as follows:

$$\ln \text{Price}_{ijt} = \beta_0 + \beta_1 \text{Dis\_inciner}_{ist} + \lambda_k \sum_{k \geq -6}^{13} Q_{ijt}^k + \beta_2 H_i + \delta_k + \gamma_t + \theta_{ct} + \epsilon_{ijt} \tag{3}$$

where Q_{ijt}^k corresponds to a set of interactions between Dis_inciner and month-to-completion dummies. Since the amount of data at one-month level is relatively small, following Bahar et al. (2021) and Bosch and Campos-Vazquez (2014), we aggregate data at two-month level to demonstrate the dynamics of the effect of CIEN on the housing price gradient. Suppose that p_i is the month when IEN completes, we further define $Q_{ijt}^k = 1$, if $t - p_i = 2k$ or $2k + 1$, and 0 otherwise, $k =$

[9] To ensure sufficient observations within each distance segment, the interval is set at 2 km (Rivera and Loveridge, 2022). The number of observations for the 0-2 km, 2-4 km, 4-6 km, 6-8 km, and 8-10 km segments are 1,401, 5,047, 7,658, 10,421, and 10,765, respectively.

$-6, -5, -4, -3, -2, -1, 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13$. For example, we set $k = 0$ for the month of completion (i.e., the first month) and the next month, $k = 1$ for the third and fourth months, $k = 2$ for the fifth and sixth months, and so on. Additionally, D_{ijt}^{-7} equals 1 for all months that are 13 or more months before CIEN, while D_{ijt}^{13} equals 1 for all months that are 26 or more months after CIEN. The dummy for $k = -7$ is excluded from the model so that the estimated coefficients represent the treatment effects relative to the period of 13 and more months before CIEN. The parameter of interest λ_k captures the average treatment effect for each period before and after CIEN, which helps to identify the dynamics of the treatment effects. We also expect our results will hold to satisfy the parallel trends assumption that the average prices of apartments close to and farther from the plant move in parallel before CIEN, which can be deduced from the statistically insignificant coefficients of λ_k before the treatment. Fig. 2 shows a graph of the coefficients for these months, from which we can visually identify when the effects start to emerge and whether the effects are only transitory or likely to persist in the long run.

5 Results

5.1 Main results

Table 2 reports estimates of our main specification in Eq. 1. In column 1, we only control for household characteristics, business-district fixed effects, year fixed effects, and quarter fixed effects, finding a statistically significant effect of CIEN on the housing price gradient. The coefficient of *Dis_inciner*, 0.0238, indicates that before CIEN, apartments near the plants suffer devaluation. For every kilometer away from the incineration plants, housing prices on average increase by 2.38%. The coefficient of *Dis_inciner* $\times$ *Post*, -0.0144, implies that CIEN narrows the gradient by 1.44 percentage points (ppts) or 60.50% (= 0.0144/0.0238). When quarter fixed effects are replaced with month fixed effects, as shown in column 2, the magnitude of the attenuation effect decreases a little, but remains statistically significant.

Column 3 replaces quarter fixed effects with quarter-by-year fixed effects. Column 4 replaces month fixed effects with month-by-year fixed effects. The results are not very sensitive to different specifications of time fixed effects. To test whether the results found are robust to inclusion of city-specific time fixed effects, columns 5 and 6 report estimates including city-year-quarter and city-year-month fixed effects, respectively. We observe that no matter which city-specific time fixed effects are used, the results remain statistically

Table 2: The effect of CIEN on the housing price gradient

lnPrice	(1)	(2)	(3)	(4)	(5)	(6)
Dis_inciner	0.0238***	0.0237***	0.0228***	0.0227***	0.0137***	0.0138***
	(0.0025)	(0.0024)	(0.0022)	(0.0022)	(0.0021)	(0.0020)
Post	0.1502***	0.1499***	0.2150***	0.2449***	0.0140	-0.0215
	(0.0168)	(0.0168)	(0.0178)	(0.0189)	(0.0190)	(0.0266)
Dis_inciner × Post	-0.0144***	-0.0143***	-0.0126***	-0.0123***	-0.0043**	-0.0042**
	(0.0021)	(0.0021)	(0.0019)	(0.0018)	(0.0018)	(0.0017)
Room	-0.0020	-0.0020	-0.0014	-0.0016	-0.0013	-0.0015
	(0.0026)	(0.0026)	(0.0025)	(0.0025)	(0.0024)	(0.0024)
Area	0.0005***	0.0005***	0.0005***	0.0005***	0.0006***	0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Age_impute	-0.0337***	-0.0337***	-0.0368***	-0.0372***	-0.0425***	-0.0429***
	(0.0015)	(0.0015)	(0.0014)	(0.0014)	(0.0014)	(0.0013)
Age_missing	0.0983***	0.0975***	0.0935***	0.0923***	0.0477	0.0508
	(0.0316)	(0.0317)	(0.0318)	(0.0320)	(0.0307)	(0.0309)
Roughcast	-0.0687***	-0.0687***	-0.0688***	-0.0687***	-0.0642***	-0.0645***
	(0.0034)	(0.0034)	(0.0033)	(0.0033)	(0.0031)	(0.0031)
Simple decoration	-0.0527***	-0.0529***	-0.0547***	-0.0552***	-0.0622***	-0.0629***
	(0.0023)	(0.0023)	(0.0023)	(0.0022)	(0.0021)	(0.0021)
Floor	-0.0125***	-0.0125***	-0.0122***	-0.0123***	-0.0113***	-0.0113***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0011)	(0.0011)
Subway	0.0421***	0.0421***	0.0440***	0.0435***	0.0438***	0.0429***
	(0.0038)	(0.0038)	(0.0037)	(0.0036)	(0.0035)	(0.0035)
Bungalow	-0.0002	-0.0002	0.0226	0.0201	-0.0096	-0.0009
	(0.0335)	(0.0336)	(0.0315)	(0.0330)	(0.0310)	(0.0320)
Tower	-0.0398***	-0.0397***	-0.0392***	-0.0389***	-0.0402***	-0.0394***
	(0.0051)	(0.0051)	(0.0050)	(0.0050)	(0.0047)	(0.0047)
Tower_slab	0.0004	0.0006	0.0027	0.0027	-0.0078	-0.0065
	(0.0080)	(0.0080)	(0.0077)	(0.0077)	(0.0072)	(0.0072)
Dis_district	-0.0136***	-0.0136***	-0.0147***	-0.0148***	0.0016	0.0014
	(0.0019)	(0.0019)	(0.0017)	(0.0017)	(0.0023)	(0.0022)
Dis_municipal	-0.0097***	-0.0097***	-0.0094***	-0.0095***	-0.0334***	-0.0336***
	(0.0012)	(0.0012)	(0.0012)	(0.0012)	(0.0026)	(0.0023)
Hospital	0.0288***	0.0289***	0.0289***	0.0279***	0.0269***	0.0266***
	(0.0066)	(0.0066)	(0.0064)	(0.0063)	(0.0058)	(0.0057)
Household size	27.8867***	27.8393***	29.4682***	29.8784***	12.2396***	12.1941***
	(2.4189)	(2.4171)	(2.4851)	(2.4840)	(4.0234)	(3.9710)
Illiteracy rate	-8.7713***	-8.7565***	-9.2383***	-9.3728***	-3.7317***	-3.7340***
	(0.7421)	(0.7416)	(0.7622)	(0.7617)	(1.2761)	(1.2599)
lnPopulation	2.3452***	2.3466***	2.4260***	2.4629***	0.7946**	0.8131**
	(0.1590)	(0.1589)	(0.1624)	(0.1622)	(0.3727)	(0.3678)
lnDensity	-1.4193***	-1.4126***	-1.5309***	-1.5566***	-0.6827***	-0.6719***
	(0.1452)	(0.1452)	(0.1494)	(0.1493)	(0.2083)	(0.2054)
lnCrime	0.0817***	0.0806***	0.0545***	0.0507***	0.0297	0.0249
	(0.0161)	(0.0161)	(0.0159)	(0.0158)	(0.0181)	(0.0179)
Business-district FE	X	X	X	X	X	X
Quarter FE	X					
Year FE	X	X	X	X		
Month FE		X				
Quarter-by-year FE			X		X	
Month-by-year FE				X		X
City-year-quarter FE					X	
City-year-month FE						X
Constant	-51.2671***	-51.2320***	-54.1951***	-55.0304***	-15.5714*	-15.6224*
	(4.8986)	(4.8946)	(5.0258)	(5.0230)	(8.7901)	(8.6772)
Observations	34,038	34,038	34,038	34,038	34,038	34,038
R-squared	0.894	0.895	0.901	0.902	0.912	0.914

Notes: This table reports the DID estimation results of Eq. 1. The dependent variable is the logarithm of transaction price per m^2. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Standard errors in the parentheses are clustered at the community × year-month level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

significant. Our preferred estimates are presented in column 6, which includes year-month and city-year-month fixed effects to control confounding factors at a very localized geographical level. The results suggest that CIEN narrows the price gradient by 0.42 ppts or 30.43% (= 0.0042/0.0138). This means that after

CIEN, apartments near the plants still suffer devaluation, but the magnitude has declined to 69.57% of the gradient before CIEN.

To put our results in perspective, we calculate an example based on our pooled data set. Before CIEN, for an apartment with an average housing area of 79.29 m^2 and an average housing price of 41,522 CNY/m^2, the estimated price gradient for an average apartment is equivalent to 45,433 CNY per km. After CIEN, the reduction in the price gradient for an average apartment is equivalent to 13,828 CNY per km. This effect is both statistically and economically significant. In particular, in 2017 the average disposable income of an urban resident in China was 36,396 CNY, thus the reduction is approximately 37.99% of the 1-year disposable income of an urban resident in China.

5.2 Location heterogeneity effect

By adopting the ring segment measures, we find more suggestive evidence of the effect of CIEN on the housing price gradient. As shown in column 6 in Table 3, before CIEN, apartments within 2 km of the plants are sold at 17.22% lower price on average than those in the control area. Notably, this is the strongest negative effect observed, and the gaps between the four rings and the control area tend to diminish as the distance increases despite a slight upward fluctuation from 4-6 km to 6-8 km. This fluctuation could be attributed to factors such as access to amenities, which may help mitigate the negative externalities of proximity to WtE incineration plants (Martínez-Jiménez et al., 2020). For instance, the average distance from properties in the 4-6 km ring to the nearest tertiary hospital is 5.25 km, compared to 6.12 km for properties in the 6-8 km ring, suggesting that the negative externalities associated with WtE incineration plants in the 4-6 km ring might be offset to a greater extent by the positive externality caused by proximity to the tertiary hospital. Once IEN is completed, the coefficients of $Post \times Ring_i$ (i=1,2,3,4) are all positive and statistically significant, indicating that a price boost is observed in apartments within 8 km of the plants. Moreover, the varying magnitudes of the interaction term coefficients indicate that the effect of CIEN is not necessarily linear in space.

In Fig. 1, we visualize the house price gradients both before and after CIEN. The blue dots and solid line depict coefficient estimates before CIEN, the red dots and dashed line represent coefficient estimates after CIEN, and the bars denote the corresponding 90% confidence intervals. Consistent with the findings in Table 3, the estimated housing price gradients are positive and become flatter after CIEN. However, neither the slope nor its change (the gap between the two lines) is uniform. The gap between the two lines is the

Table 3: The effect of CIEN on the housing price gradient: by distance segment

lnPrice	(1)	(2)	(3)	(4)	(5)	(6)
$Ring_1$	-0.2443***	-0.2452***	-0.2284***	-0.2347***	-0.1900***	-0.1890***
	(0.0288)	(0.0285)	(0.0287)	(0.0281)	(0.0260)	(0.0253)
$Ring_2$	-0.1439***	-0.1440***	-0.1373***	-0.1355***	-0.0650***	-0.0664***
	(0.0163)	(0.0161)	(0.0144)	(0.0140)	(0.0131)	(0.0125)
$Ring_3$	-0.0742***	-0.0745***	-0.0687***	-0.0672***	-0.0531***	-0.0549***
	(0.0134)	(0.0133)	(0.0116)	(0.0114)	(0.0111)	(0.0108)
$Ring_4$	-0.1016***	-0.1020***	-0.0930***	-0.0919***	-0.0759***	-0.0763***
	(0.0118)	(0.0117)	(0.0105)	(0.0100)	(0.0103)	(0.0097)
Post	0.0128	0.0131	0.0959***	0.1298***	-0.0351**	-0.0682***
	(0.0102)	(0.0102)	(0.0137)	(0.0159)	(0.0151)	(0.0246)
Post $\times$ $Ring_1$	0.1559***	0.1561***	0.1355***	0.1409***	0.1016***	0.0984***
	(0.0282)	(0.0278)	(0.0281)	(0.0276)	(0.0254)	(0.0248)
Post $\times$ $Ring_2$	0.1015***	0.1007***	0.0917***	0.0891***	0.0225*	0.0225**
	(0.0150)	(0.0148)	(0.0132)	(0.0129)	(0.0119)	(0.0114)
Post $\times$ $Ring_3$	0.0298**	0.0297**	0.0199*	0.0179*	0.0090	0.0105
	(0.0125)	(0.0124)	(0.0107)	(0.0105)	(0.0102)	(0.0100)
Post $\times$ $Ring_4$	0.0611***	0.0613***	0.0502***	0.0485***	0.0373***	0.0375***
	(0.0116)	(0.0115)	(0.0103)	(0.0098)	(0.0101)	(0.0096)
Control variables	X	X	X	X	X	X
Business-district FE	X	X	X	X	X	X
Quarter FE	X					
Year FE	X	X	X	X		
Month FE		X				
Quarter-by-year FE			X		X	
Month-by-year FE				X		X
City-year-quarter FE					X	
City-year-month FE						X
Constant	-47.5312***	-47.4748***	-50.5941***	-51.1853***	-9.0290	-9.1305
	(5.0734)	(5.0697)	(5.2234)	(5.2044)	(8.8240)	(8.7332)
Observations	34,038	34,038	34,038	34,038	34,038	34,038
R-squared	0.895	0.895	0.902	0.903	0.912	0.914

Notes: This table reports the DID estimation results of Eq. 2. The dependent variable is the logarithm of transaction price per m^2. Housing characteristics and controls at the district level are included in all specifications. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Standard errors in the parentheses are clustered at the community $\times$ year-month level. The coefficient of each ring segment (dummy variable) demonstrates an effect in the percentage calculated as [exp (coefficient)-1] according to Halvorsen and Palmquist (1980). $Ring_5$, Post $\times$ $Ring_5$ are omitted as $Ring_5$ acts as the reference category. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

largest between 0-2 km of the plants, implying that the reduction in the housing price gradient is stronger for apartments particularly near the plants, which offers additional supportive evidence for the concern mitigation mechanism in Section 5.5.

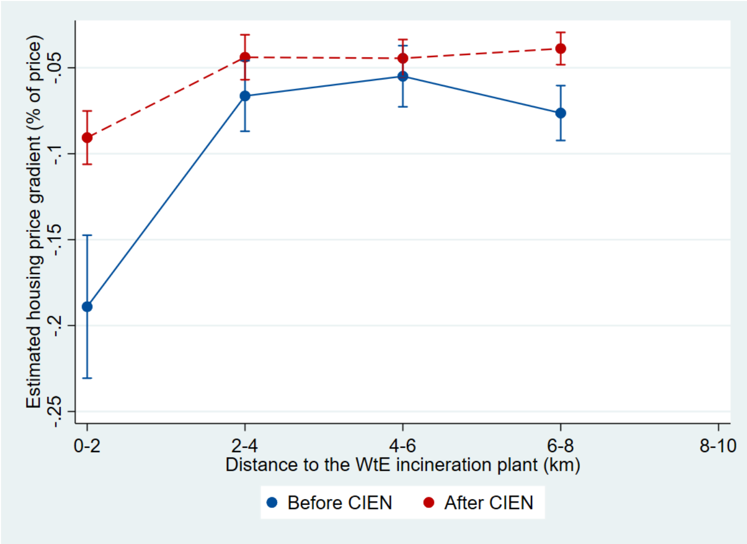

Fig. 1: Housing price gradients before and after CIEN: estimates by distance segment.
Notes: The plot depicts the estimated housing price gradients by distance segment (0–2 km, 2–4 km, 4–6 km, 6–8 km, 8–10 km) from Eq. 2, both before and after CIEN. The dependent variable is the logarithm of transaction price per m^2. Housing characteristics and controls at the district level are included. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Vertical bars denote 90% confidence intervals.

5.3 Event study analysis

In order to test if the parallel trends assumption holds and to explore dynamic treatment effects, we estimate the event study specification described in Eq. 3. As shown in Table 4, the effects on the housing price gradient before CIEN are all not statistically different from zero. We perform F-tests and cannot reject the null hypothesis at conventional confidence levels, that all lead coefficients are not statistically different from zero [F-Stat = 0.63, p-value = 0.6743]. We also test if all lag coefficients are jointly equal to zero and are able to reject the null hypothesis at 10% level of confidence [F-Stat = 1.68, p-value = 0.0573]. These results suggest that the parallel trends assumption is satisfied. We further plot all lead and lag coefficients along with the 90% confidence bands in Fig. 2 to visualize the dynamic effects. Again, it can be seen that all lead coefficients are statistically indistinguishable from zero, satisfying the parallel trends assumption. Notably, the effect of CIEN on the housing price gradient starts to emerge ten months after the completion. This is consistent with the notion that the dissemination of IEN information, as well as public adaptation to it, all takes time. When residents observe on the ground that the plants are disclosing their emissions information in real time through the display screens at the entrances and find that they are consistently operating in compliance with emissions standards, their concerns begin to be eased, and they update their perceptions of the risks posed by the WtE incineration plants. From the tenth month after CIEN onward, all the coefficients for post-treatment periods are statistically significant, indicating that the effect of CIEN on the housing price gradient persists for the whole post-treatment window. Specifically, the effect first rises from 0.49 ppts in the tenth month to the crest of 0.93 ppts in the fourteenth month after CIEN, then declines to 0.68 ppts in the sixteenth month after CIEN and remains relatively stable at this level afterwards.

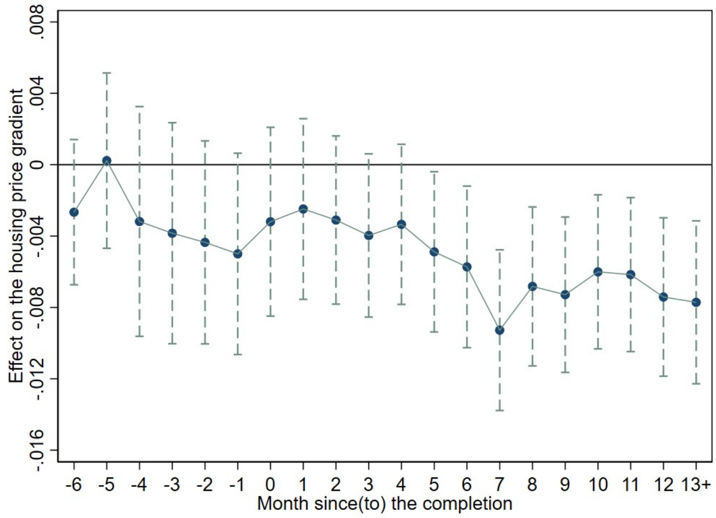

Fig. 2: Event study on the housing price gradient.
Notes: The horizontal axis measures the number of months since IEN is completed. The plots connected by the solid line indicate the estimated effect for each period. The reference category consists of all observations transacted thirteen or more months before CIEN. See Table 4 for the exact values of these point estimates. The vertical bars indicate the 90% confidence intervals.

5.4 Robustness tests

The previous results show plausible evidence of the effect of CIEN on the housing price gradient. In this section, we present robustness tests and falsification tests to address potential concerns about our identification strategy.

Randomly assigning completion time of IEN. To evaluate the omitted-variables problems in our baseline results, we conduct a simulation-based placebo test by randomly assigning the time of CIEN (Chetty et al., 2009; La Ferrara et al., 2012). Specifically, we draw 500 sets of placebo completion dates, where each observation is assigned to a random month during our sample period. We then estimate the treatment effect coefficients from Eq. 1 for each set of these placebo dates. As Fig. B1 shows, the mean of the estimates obtained from random assignments is close to zero. Meanwhile, less than 9% of the estimates are below our true baseline estimates in Table 2, column 6. This suggests that when random months are applied, some of which may coincide by chance with the months of other ongoing interventions (if they exist), the effect we observe won't be as strong. Therefore, the simulation results prove the robustness of the conclusion that CIEN has significantly flattened the housing price gradient. We also set the time of CIEN to one year and

Table 4: An event study: the effects of CIEN on the housing price gradient

lnPrice	(1)
Dis_inciner	0.0156***
	(0.0027)
12 months before completion	-0.0027
	(0.0025)
10 months before completion	0.0002
	(0.0030)
8 months before completion	-0.0032
	(0.0039)
6 months before completion	-0.0038
	(0.0038)
4 months before completion	-0.0044
	(0.0035)
2 months before completion	-0.0050
	(0.0034)
Month of completion	-0.0032
	(0.0032)
2 months after completion	-0.0025
	(0.0031)
4 months after completion	-0.0031
	(0.0029)
6 months after completion	-0.0040
	(0.0028)
8 months after completion	-0.0033
	(0.0027)
10 months after completion	-0.0049*
	(0.0027)
12 months after completion	-0.0057**
	(0.0028)
14 months after completion	-0.0093***
	(0.0027)
16 months after completion	-0.0068**
	(0.0027)
18 months after completion	-0.0073***
	(0.0026)
20 months after completion	-0.0060**
	(0.0026)
22 months after completion	-0.0062**
	(0.0026)
24 months after completion	-0.0074***
	(0.0027)
26 months after completion	-0.0077***
	(0.0028)
Control variables	X
Business-district FE	X
Month-by-year FE	X
City-year-month FE	X
Constant	-15.4054*
	(8.6601)
Observations	34,038
R-squared	0.914

Notes: This table reports the DID estimation results of Eq. 3. The dependent variable is the logarithm of transaction price per m^2. The regression controls for housing characteristics and controls at the district level. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Standard errors in the parentheses are clustered at the community × year-month level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

half a year before the actual time as fake completion times, and model (1) is re-estimated using the observations prior to CIEN. The coefficients of *Dis_inciner* × *Post* in Supplementary Appendix Table B1, columns

1-2 are all statistically indistinguishable from zero, increasing our confidence that the baseline results are not spurious.

Excluding plants with few observations before CIEN. In our dataset, Beijing Beikong Green Sea Energy Environmental Protection Co., Ltd. (Sujiatuo Plant) was put into operation in March, 2017 and does not have too many observations prior to CIEN. We remove this plant and rerun the regression. Results in Supplementary Appendix Table B1, column 3 suggest that our results are robust to excluding plants with relatively few observations before the completion.

Checking for anticipation effects. Given that the policy was released in April 2017 and it took time for WtE incineration plants to finally complete the tasks of IEN after their receipt of the policy, one might be concerned that there exist anticipation effects prior to the actual completion. The results in the test for parallel trends assumption have verified that no anticipation effects exist. We conduct an additional test to provide more suggestive evidence. An indicator named *Post_issue* is constructed, which equals 1 when the transaction occurs during the announcement period,[10] and introduce the interaction between *Dis_inciner* and *Post_issue* into the baseline regression. As reported in column 4 of Supplementary Appendix Table B1, the coefficient of *Dis_inciner* $\times$ *Post_issue* is statistically indistinguishable from zero, indicating that the issuance of the policy elicits no effect on the housing price gradient.

Checking for the demographic characteristics. There might be concerns that the decrease in the housing price gradient is caused by changes in the demographic characteristics of the residents around the plants after CIEN. Specifically, men are more likely to accept potential environmental risks than women (Filippin and Crosetto, 2016; Post et al., 2020). In addition, younger people generally demonstrate a higher level of acceptance towards environmental infrastructures (Opper et al., 2016). Therefore, we examine the demographic characteristics before and after CIEN to rule out the possibility that the flattened housing price gradient is driven by people with higher level of acceptance starting to crowd in around the plants after CIEN. Supplementary Appendix Table B2 displays t-tests of means for the above demographic characteristics in pre-treatment and post-treatment groups. The results suggest that the proportion of women in the post-treatment group is higher than that in the pre-treatment group at the 5% significance level. If our results are driven by the changing gender ratio, the price gradient would become steeper rather than flatter, thus this possibility is ruled out. Turning our eyes to the proportion of the young people (those who are below 30), although it is higher in the post-treatment group than that in the pre-treatment group, we further

[10] We define the period from policy issuance to CIEN as the announcement period.

find in this age category that the proportion of women is 7.3% higher in the post-treatment group than that in the pre-treatment group, which may partially offset the impact of the higher proportion of young people after CIEN. Overall, these results provide suggestive evidence that the flattened housing price gradient is not likely to be caused by a demographic shift.

Using housing transaction data near plants that came into operation after CIEN. If CIEN is effective in attenuating the housing price gradient, we would expect the housing prices near the plants that came into operation after CIEN to be less negatively impacted. To this end, we investigate the housing prices near the plants that came into operation after CIEN. 1,031 transaction data within 10 km of 5 WtE incineration plants are obtained.[11] Removing the DID design, we run an OLS linear regression on these data, with *lnPrice* as the dependent variable and *Dis_inciner* as the independent variable. All the control variables included in the baseline specification are introduced into the OLS regression. The coefficients of *Dis_inciner* in Supplementary Appendix Table B3 are all positive but not statistically significant, indicating that after CIEN, proximity of the communities to the plants does not have negative impacts on housing prices. These results provide relatively strong evidence that CIEN mitigates residents' concerns towards the plants to a large extent.

Alternative time periods. The period for our analysis is relatively short to reduce the possibility that potential unobservable differences that could be influencing our results are accounted for. We further limit the sample period both before and after CIEN to reduce the possibility of capturing the contemporaneous changes in unobservable variables at the community level. We limit the sample period to a three-year window (one and a half years before and after CIEN) and a two-year window (one year before and after CIEN).[12] Results in Supplementary Appendix Table B4, columns 1-2 show that the attenuation effects on the housing price gradient are still negative and statistically significant, with the magnitudes being slightly larger compared to the baseline estimate in Table 2, column 6.

Alternative specifications of time fixed effects. In the main analysis, we include city-year-month fixed effects to control for any city-wide policy impacts and time patterns. We replace the city-year-month fixed effects with city-specific linear time trends and also include city-specific quadratic time trends. As reported in Supplementary Appendix Table B5, columns 1 and 2, our coefficient of interest is still negative and statistically significant.

[11] Supplementary Appendix C describes the process by which these plants are identified as ideal for this robustness test and depicts the characteristics of the plants.

[12] Considering that it takes nearly 10 months to observe a significant decrease in the housing price gradient after CIEN, we do not limit the time period to a one-year window (half a year before and after CIEN).

Alternative cluster level. In the baseline specification, we correct errors for heteroskedasticity and serial correlation by clustering at the community-year-month level. We also cluster standard errors at alternative levels to control for correlation of housing prices under different levels. Specifically, we test other forms of two-way clustering, i.e., district-year-month, city-year-month, community-year-quarter, district-year-quarter, and city-year-quarter. The results are shown in Supplementary Appendix Table B6, columns 1-5, and the attenuation effect of CIEN on the housing price gradient is still robust.

Accounting for omitted variable bias. Following the method proposed by Oster (2019) which exploits insights from Altonji et al. (2005), we perform a robustness test for omitted variable bias. The results are presented in Supplementary Appendix Table B7. We first reproduce the baseline results in the top row. The second row then report estimation bounds where $R_{\max}$ is defined as 1.[13] An estimated bounded set that excludes zero can be considered an indication of robust effects that are non-zero. The bottom row presents Oster's delta, which indicates how much larger the selection on unobservables would have to be compared to the selection on observables for the true effect to be zero. A positive ratio greater than one suggests that selection on unobserved variables must be greater than selection on observed variables to fully explain the estimated effect, which is unlikely to be the case when a large set of covariates are controlled. A negative ratio suggests that the estimated effect is biased downward and that adding more controls could make the coefficient larger (Satyanath et al., 2017). We find that the coefficient is reduced to -1.2268, smaller than the coefficient in Table 2, column 6, and the estimated bound determined by the lower and upper bounds does not contain zero.[14] Moreover, the value of Oster's delta is -0.05603, denoting that the estimated treatment effect is unlikely to be driven by unobserved variables.

5.5 Mechanism analysis

5.5.1 Concern mitigation mechanism

One of the core measures of IEN is to set up electronic displays at the entrances of the plants and disclose the emissions data of the plants to the public in real time. In this way, residents living in close proximity or having easy access to the plants will be more likely to learn about the plants' pollutant emissions and have a better understanding of the plants' operational status, thereby reducing their fear of the unknown

[13] Oster (2019) suggest that the maximum R^2 is assumed as 1.3 times the R^2 reported in the regression with the full set of observables. Considering our relatively high R^2 in our baseline estimates (more than 0.9), R^2 is assumed as 1.

[14] The result that the treatment effect is much larger than the controlled treatment effect is reasonable because both baseline and fully controlled regressions have R^2 greater than 0.8, suggesting that the DID variable can explain the majority of the change in the housing price gradient.

and lowering their perceptions of risks (Gayer et al., 2000; Tanaka and Zabel, 2018). Thus, we would expect a higher decrease in the housing price gradient among these communities. To prove the concern mitigation mechanism, we construct a variable named *Access*, whose value is assigned based on the difficulty degree for residents to approach the plants considering factors such as distance and transportation availability.[15] We further develop the interaction term between *Access* and *Dis_inciner* × *Post*. Results in Table 5, column 1 suggest that the housing price gradient in communities that have easier access to the plants narrows more after CIEN, supporting the concern mitigation mechanism. Moreover, the findings from Fig. 1 reinforces this mechanism. It can be seen that the decline in the housing price gradient is more pronounced for apartments within 0-2 km of the plants. This pattern suggests that residents with easier access to the real-time emissions information are more likely to have their concerns alleviated, providing supportive evidence for the concern mitigation mechanism.

Table 5: Results of mechanism analysis.

lnPrice	(1) Access	(2) Environmental improvement
Dis_inciner	0.0128***	0.0140***
	(0.0020)	(0.0020)
Post	-0.0106	-0.0223
	(0.0269)	(0.0266)
Dis_inciner × Post	-0.0056***	-0.0039**
	(0.0017)	(0.0017)
Dis_inciner × Post × Access	-0.0090***	
	(0.0023)	
Dis_inciner × Post × Wind		-0.0010
		(0.0009)
Control variables	X	X
Business-district FE	X	X
Month-by-year FE	X	X
City-year-month FE	X	X
Constant	-16.9262*	-15.2760*
	(8.6960)	(8.6970)
Observations	34,038	34,038
R-squared	0.914	0.914

Notes: The dependent variable is the logarithm of transaction price per m^2. Housing characteristics and controls at the district level are included in all specifications. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Standard errors in the parentheses are clustered at the community × year-month level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

5.5.2 Environmental improvement mechanism

The externalities associated with WtE incineration plants derive partly from the poorer air quality caused by incineration. By setting up electronic displays at plant entrances and realizing the networking of the automatic monitoring equipment with environmental protection departments, both public monitoring and

[15] See Supplementary Appendix D for the description of the *Access* variable.

government regulation would be strengthened, forcing the plants to standardize their operation, thus the pollutant emissions from these plants might be reduced. In this way, the environmental quality after CIEN might be improved and contribute to the attenuation of the housing price gradient. As the emissions data for these plants prior to CIEN are not available, we could not directly compare the environmental performance of these plants before and after CIEN. However, we could use data on wind direction to provide suggestive evidence for the environmental improvement mechanism. Given that the trajectory of emissions can be drastically affected by wind direction, if environmental improvement is a mechanism, the communities located downwind to the plants would benefit more from CIEN, and a higher decrease in the price gradient would be expected among these communities. To examine this mechanism, we first gather the wind direction data for 2015-2019 from China Meteorological Data Service Centre[16] to obtain the wind directions with the greatest number of occurrences in 12 months before the transaction. Following the procedure detailed in Rangel and Vogl (2019), communities located downwind to the plants are defined as those within a 45-degree central angle from these opposite directions (hereafter, downwind communities).[17] We calculate the azimuth of each community relative to the corresponding plant by geographic coordinates to identify the downwind communities. A variable named *Wind* is constructed, which equals 1 when the community is a downwind one. The *Wind* variable is then interacted with $Dis\_inciner \times Post$. As shown in Table 5, column 2, the coefficient of the triple interaction term is not statistically significant, indicating that the housing price gradient in the downwind direction does not narrow more after CIEN than it does in other directions, ruling out the environmental improvement mechanism.

Overall, these results lend credibility to the hypothesis that the mitigation of concerns is a potential mechanism behind the impact of CIEN on property prices.

5.6 Heterogeneity analysis

We next explore how the effects of CIEN on the housing price gradient vary along regional attributes and plant characteristics. In Supplementary Appendix Table F1, we examine the effect heterogeneity by introducing triple interactions between *Dis_inciner*, *Post*, and area- level or plant- level moderators.

Urban area vs. Suburban area. We first investigate the effect heterogeneity across different areas regarding whether the transaction occurs in urban areas or suburban areas. We introduce an interaction between $Dis\_inciner \times Post$ and *Urban*, which is an indicator of whether the housing transaction occurs in the

[16] Website: https://data.cma.cn.
[17] See Supplementary Appendix E for an illustration of the range of downwind communities.

urban area or suburban area. The coefficient of *Dis_inciner* × *Post* × *Urban* is negative and statistically significant, indicating that the flattening effect is stronger for urban areas. This might be due to the fact that urban areas tend to be populated by better-educated, professionally stable residents (Zahl-Thanem and Rye, 2024), who tend to be more sensitive to environmental issues and better able to understand environmental information. In contrast, suburban areas may have a higher proportion of lower-income residents whose primary concerns are often economic rather than environmental (Liu and Bardaka, 2021). As a result, even when environmental data is publicly available, suburban residents may exhibit lower levels of concern, which reduces the effectiveness of disclosure in alleviating their worries.

Old plants vs. new plants. We next investigate whether the flattening effect varies among plants with different ages. We sort plants into two subgroups based on their average age and introduce an interaction between *Dis_inciner* × *Post* and *Old*, which is an indicator of whether the plant was put into operation in earlier years. As shown in column 2, the coefficient for *Dis_inciner* × *Post* × *Old* is negative and statistically significant, indicating that the earlier the plant was built, the greater the flattening effect of CIEN on the housing price gradient. A possible interpretation is that, as the incineration technology of the older plants may not be so mature and advanced (Song et al., 2023), whether the plants meet the emission standards has always been a major concern for residents living near older plants (Chen et al., 2010). When the government makes the emissions data available to the public through IEN, residents' concerns are responded to in the most direct way, thus the gradient in the vicinity of these older plants drops even more.

High treatment capacity vs. Low treatment capacity. We further investigate whether the effect varies among plants with different treatment capacities. We sort plants into two subgroups based on their average treatment capacity and introduce an interaction between *Dis_inciner* × *Post* and *High capacity*, which is an indicator of whether the plant has higher treatment capacity. The coefficient of the triple interaction term in column 3 is positive and statistically significant, indicating that the flattening effect is smaller when the plant's treatment capacity is higher. This is in line with our intuition that residents generally have deeper concerns about plants with larger sizes (Ready, 2010), thus their concerns are more difficult to be alleviated by CIEN, resulting in a less significant effect of CIEN on the gradient.

High flue gas abatement control ability vs. Low flue gas abatement control ability. We finally investigate the effect heterogeneity across different plants regarding the flue gas abatement control abilities. We gather the ranking of the flue gas abatement control abilities of the plants and generate a dummy variable named

Ranking.[18] Interacting this variable with *Dis_inciner* × *Post*, we find in column 4 that the coefficient of the triple interaction term is positive and statistically significant, indicating that when the ranking value of the abatement control ability of the plant is larger, that is, when the plant's flue gas abatement control ability becomes lower, the flattening effect on the price gradient will be weakened. This is also in line with our intuition that when the plants have higher flue gas abatement control abilities, residents' concerns are more easily to be mitigated (Wang et al., 2021), leading to a more significant smoothing effect on the housing price gradient.

6 Discussion and conclusions

Due to the inherent concerns about potential health risks from incineration, coupled with low levels of information transparency, residents often hold strong NIMBY attitude towards WtE incineration plants in their vicinity. To mitigate NIMBYism concerns, some local governments have begun to implement information disclosure policies. However, the effectiveness of such policies is not clear. Using the 2017 IEN policy as a shock to residents' risk perceptions and taking advantage of spatial variations in the resale prices of apartments at different distances to the same plant, this study investigates the effectiveness of the information disclosure policy regarding WtE incineration plants in alleviating NIMBYism concerns from the perspective of housing prices. The results suggest that when IEN is completed, the housing price gradient with respect to distance within 10 km from the plants is attenuated by 30.43%, indicating that households temper their aversion to the plants once they are provided with relevant information. The gradient reduction is approximately 38% of the 1-year disposable income of an urban resident in China. The event study analysis shows that the property prices start to respond to the shock 10 months after CIEN and the effect on the housing price gradient persists once manifested. The validation of the causal effect of CIEN is verified through a set of robustness tests and placebo tests. Moreover, we find that CIEN has stronger effects on the housing price gradient for urban areas and when the plants are older, have lower capacities, and have higher flue gas abatement control abilities.

Our study yields important insights for policy makers. On the one hand, our findings demonstrate that information disclosure can effectively mitigate NIMBYism concerns. Therefore, it is necessary for the government to firmly implement information disclosure policies and ensure real-time emissions data disclosure, to effectively alleviate the NIMBY effect and further transform it to Please in My Backyard (PIMBY), which is

[18] See Supplementary Appendix G for the description of the *Ranking* variable.

used to describe residents' favorable sentiments towards local development near where they live (Jerolmack and Walker, 2018). Furthermore, this practice should not be confined to incineration plants but should also be applied to other environmental infrastructure, such as wastewater treatment and hazardous waste sites, to promote sustainable urban development.

It is also worth noting that the housing price gradient is not completely flattened after CIEN, which implies that NIMBYism concerns have only been alleviated to a certain extent rather than entirely. Therefore, additional measures are needed to further eliminate residents' concerns. First, the government should increase the level of information disclosure regarding the plants. In addition to erecting electronic display screens at plant entrances, the government should also encourage environmental protection departments to implement supervisory monitoring of the plants. Both environmental protection departments and incineration plants should enhance the construction, operation, and maintenance of information disclosure platforms, promoting the full disclosure of supervisory monitoring data and self-monitoring data to the public. Second, it is crucial for the government to ensure the reliability of the disclosed information. The government should conduct big data analyses of the automatic monitoring data from the plants and identify those whose data are suspected of being abnormal or falsified. Unannounced and random spot checks should be carried out periodically, and any plants that falsify data should be strictly held accountable. Third, it is recommended to mobilize residents to form monitoring groups to conduct random inspections on plant operations. This initiative would make plant operations more transparent to the public, thus enhancing public trust in the plants.

On the other hand, while our study focuses on 13 cities in China, the above-mentioned strategies are likely applicable to cities across China and other countries that are experiencing similar opposition to environmental projects. China has witnessed numerous NIMBY movements in recent years, not only in large cities such as Shanghai and Shenzhen, but also in small and medium-sized cities (Xin and Wan, 2023). Even in developed countries, a series of protests against NIMBY facilities have taken place in the UK (Kirkman and Voulvoulis, 2017), America (Hess et al., 2022), and Japan (Uji et al., 2021). In this sense, the combination of information disclosure, regulatory oversight, and public engagement can provide a useful reference for cities throughout China and other countries to address NIMBYism concerns, which has become an issue of growing global concern.

The study also has some limitations that warrant further research. First, the transaction data from the trading system has few statistics on homebuyers, such as their profession and attitudes towards the implementation of IEN. Conducting a questionnaire survey among households in the sample area would provide valuable insights into the positive benefits of information disclosure from a consumer psychology perspective. Second, we use data on wind direction to provide suggestive evidence for ruling out the environmental improvement mechanism. If emissions information before CIEN becomes available in the future, a direct examination of the environmental improvement mechanism could be conducted. Finally, due to scarce observations around certain plants and data limitation, our samples only cover 13 plants from 7 cities. Future studies could expand the sample size to enhance the credibility of the results if related data are available.

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Appendix A Variable descriptions

Table A1: The characteristics of the WtE incineration plants

City	WtE incineration plant	Commencement date of operation	Completion date of IEN	Daily treatment capacity (tons/day)
Beijing	Beijing Beikong Green Sea Energy Environmental Protection Co., Ltd. (Sujiatuo Plant)	March 9, 2017	August 23, 2017	2100
Hangzhou	Hangzhou Green Energy Environmental Protection Power Co., Ltd.	October 1, 2004	July 31, 2017	450
Xiamen	Xiamen Environment and Energy Investment Development Co., Ltd. Haicang Plant	January 3, 2015	July 31, 2017	1850
Shanghai	Shanghai Dongshitang Waste-to-energy Co., Ltd.	June 2, 2016	August 23, 2017	1000
Shanghai	Shanghai Huancheng Waste-to-energy Co., Ltd. (Jiangqiao Plant)	January 1, 2015	August 23, 2017	1500
Shanghai	Shanghai Laogang Solid Waste Comprehensive Development Co.Ltd.	May 1, 2013	August 23, 2017	3000
Shanghai	Shanghai Liming Resources Recycling Co., Ltd.	July 1, 2014	August 23, 2017	2000
Shanghai	Shanghai Pucheng Thermal Power Energy Co., Ltd. (Yuqiao Plant)	May 29, 2002	August 23, 2017	1050
Shanghai	Shanghai Tianma Waste-to-energy Co., Ltd.	April 25, 2016	August 23, 2017	3500
Suzhou	Everbright Environmental Energy Suzhou Co., Ltd.	July 18, 2017	December 31, 2017	5800
Tianjin	Tianjin Chenxinglike Environmental Protection Technology Development Co., Ltd.	November 1, 2007	August 23, 2017	1250
Wuhan	Wuhan Borui Environmental Protection Energy Development Co., Ltd. (Guodingshan Plant)	October 20, 2014	September 30, 2017	1680
Wuhan	Wuhan Hankou Green Energy Co., Ltd.	December 20, 2010	September 30, 2017	2000

Appendix B Robustness tests

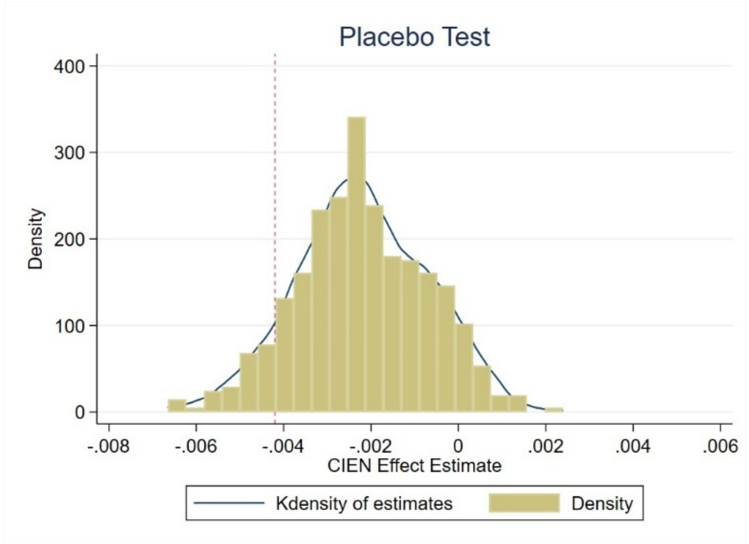

Fig. B1: Placebo test with completion months randomly assigned.
Notes: The figure shows the probability distribution of the estimated coefficients from 500 simulations randomly assigning the time of CIEN. The red vertical line indicates the estimate obtained from estimating the effect using the correct month, that is, it takes the value that appears in Table 2, column 6.

Table B1: Robustness tests for randomly assigning the time of CIEN, excluding plants with few observations before CIEN, and checking for anticipation effects

lnPrice	(1) One year before CIEN	(2) Half a year before CIEN	(3) Excluding Beijing	(4) Anticipation effect
Dis_inciner	0.0321***	0.0315***	0.0135***	0.0144***
	(0.0047)	(0.0045)	(0.0020)	(0.0022)
Post_1	0.1127***			
	(0.0285)			
Dis_inciner × post_1	-0.0037			
	(0.0030)			
Post_2		0.0338		
		(0.0395)		
Dis_inciner × Post_2		-0.0032		
		(0.0032)		
Post			-0.0201	-0.0507
			(0.0271)	(0.0446)
Dis_inciner × Post			-0.0042**	-0.0048**
			(0.0017)	(0.0019)
Post_issue				-0.0098
				(0.0395)
Dis_inciner × Post_issue				-0.0035
				(0.0031)
Control variables	X	X	X	X
Business-district FE	X	X	X	X
Month-by-year FE	X	X	X	X
City-year-month FE	X	X	X	X
Constant	2,960.3444***	3,143.8046***	-18.4296**	-15.5991*
	(1,021.6562)	(1,039.3245)	(8.9607)	(8.6718)
Observations	4,757	4,757	33,731	34,038
R-squared	0.903	0.903	0.914	0.914

Notes: The dependent variable is the logarithm of transaction price per m^2. Housing characteristics and controls at the district level are included in all specifications. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Standard errors in the parentheses are clustered at the community × year-month level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B2: Means of demographic characteristics in pre-treatment and post-treatment groups

	Means		Difference in Means	p-value
	Pre-treatment	Post-treatment		
Gender				
Female %	0.387	0.415	-0.028	0.011
Observations	15162	-	-	-
Age				
Young %	0.180	0.305	-0.125	0.000
Observations	15130	-	-	-
Gender & Age				
Female & Young %	0.358	0.430	-0.073	0.004
Observations	4330	-	-	-

Table B3: The effect of proximity of the communities to the plants on housing prices

lnPrice	(1)	(2)	(3)	(4)	(5)	(6)
Dis_inciner	0.0115	0.0123	0.0115	0.0131	0.0130	0.0155
	(0.0093)	(0.0092)	(0.0093)	(0.0093)	(0.0094)	(0.0095)
Room	0.0551***	0.0560***	0.0551***	0.0554***	0.0556***	0.0557***
	(0.0128)	(0.0127)	(0.0128)	(0.0125)	(0.0131)	(0.0131)
Area	-0.0028***	-0.0028***	-0.0028***	-0.0028***	-0.0029***	-0.0028***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Age_impute	-0.0467***	-0.0466***	-0.0467***	-0.0467***	-0.0467***	-0.0466***
	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0065)	(0.0066)
Age_missing	-0.0583	-0.0563	-0.0583	-0.0567	-0.0606	-0.0617
	(0.0538)	(0.0536)	(0.0538)	(0.0538)	(0.0544)	(0.0566)
Roughcast	-0.0455**	-0.0491***	-0.0455**	-0.0514***	-0.0469**	-0.0519***
	(0.0180)	(0.0186)	(0.0180)	(0.0189)	(0.0183)	(0.0197)
Simple decoration	-0.0438***	-0.0449***	-0.0438***	-0.0450***	-0.0448***	-0.0452***
	(0.0101)	(0.0099)	(0.0101)	(0.0099)	(0.0100)	(0.0100)
Subway	0.0654***	0.0652***	0.0654***	0.0660***	0.0625***	0.0650***
	(0.0223)	(0.0221)	(0.0223)	(0.0220)	(0.0222)	(0.0224)
Floor	-0.0398***	-0.0398***	-0.0398***	-0.0398***	-0.0395***	-0.0393***
	(0.0066)	(0.0066)	(0.0066)	(0.0066)	(0.0065)	(0.0065)
Bungalow	0.0508**	0.0618	0.0508**	0.0583	0.0390	0.0357
	(0.0255)	(0.0390)	(0.0255)	(0.0411)	(0.0316)	(0.0403)
Tower	0.1630***	0.1596***	0.1630***	0.1590***	0.1641***	0.1706***
	(0.0373)	(0.0358)	(0.0373)	(0.0354)	(0.0369)	(0.0373)
Tower_slab	0.0550*	0.0557*	0.0550*	0.0551*	0.0574**	0.0521*
	(0.0288)	(0.0284)	(0.0288)	(0.0285)	(0.0288)	(0.0290)
Dis_district	-0.0109	-0.0104	-0.0109	-0.0096	-0.0090	-0.0076
	(0.0084)	(0.0085)	(0.0084)	(0.0084)	(0.0086)	(0.0086)
Dis_municipal	-0.0130*	-0.0124*	-0.0130*	-0.0124*	-0.0128*	-0.0123*
	(0.0069)	(0.0068)	(0.0069)	(0.0068)	(0.0069)	(0.0069)
Hospital	-0.0459	-0.0383	-0.0459	-0.0355	-0.0315	-0.0217
	(0.0504)	(0.0507)	(0.0504)	(0.0508)	(0.0504)	(0.0521)
Household size	-26.8949***	-26.0201***	-26.8949***	-24.9502***	-23.9354***	-29.7188**
	(4.7682)	(4.7601)	(4.7682)	(5.2170)	(5.2251)	(12.0987)
Illiteracy rate	3.5929***	3.4758***	3.5929***	3.3271***	3.1802***	3.9816**
	(0.6173)	(0.6160)	(0.6173)	(0.6797)	(0.6892)	(1.6531)
lnPopulation	-6.6011***	-6.3751***	-6.6011***	-5.9465***	-5.8110***	-6.8241**
	(0.8235)	(0.8194)	(0.8235)	(1.0662)	(0.8847)	(2.6997)
lnDensity	6.8853***	6.7202***	6.8853***	6.4501***	6.2979***	7.0321***
	(0.7151)	(0.7117)	(0.7151)	(0.8347)	(0.7714)	(1.9424)
lnCrime	0.0282	0.0529	0.0282	0.0781	0.1701	-0.3428
	(0.3509)	(0.3517)	(0.3509)	(0.3589)	(0.4105)	(0.8477)
Business-district FE	X	X	X	X	X	X
Quarter FE	X					
Year FE	X	X	X	X		
Month FE		X				
Quarter-by-year FE			X		X	
Month-by-year FE				X		X
City-year-quarter FE					X	
City-year-month FE						X
Constant	117.1331***	112.8347***	117.1440***	106.0439***	102.3102***	128.1229**
	(18.9260)	(18.8674)	(18.9203)	(22.3656)	(20.8591)	(57.3733)
Observations	997	997	997	997	997	997
R-squared	0.962	0.963	0.962	0.963	0.963	0.964

Notes: The dependent variable is the logarithm of transaction price per m^2. Standard errors in the parentheses are clustered at the community × year-month level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B4: Robustness tests for alternative time periods

lnPrice	(1) Three-year window	(2) Two-year window
Dis_inciner	0.0146***	0.0126***
	(0.0023)	(0.0028)
Post	-0.0146	-0.0175
	(0.0266)	(0.0276)
Dis_inciner × Post	-0.0051***	-0.0048**
	(0.0019)	(0.0023)
Control variables	X	X
Business-district FE	X	X
Month-by-year FE	X	X
City-year-month FE	X	X
Constant	-8.4768	24.2348*
	(9.7376)	(13.4768)
Observations	20,672	12,582
R-squared	0.915	0.916

Notes: The dependent variable is the logarithm of transaction price per m^2. Housing characteristics and controls at the district level are included in all specifications. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Standard errors in the parentheses are clustered at the community × year-month level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B5: Robustness tests for alternative specifications of time fixed effects

lnPrice	(1) Linear time trends	(2) Quadratic time trends
Dis_inciner	0.0174***	0.0187***
	(0.0020)	(0.0020)
Post	0.0806***	0.0938***
	(0.0191)	(0.0186)
Dis_inciner × Post	-0.0069***	-0.0087***
	(0.0017)	(0.0017)
Control variables	X	X
Business-district FE	X	X
Month-by-year FE	X	X
City-specific linear time trends	X	X
City-specific quadratic time trends		X
Constant	-29.4961***	-207.4264***
	(7.0099)	(26.3290)
Observations	34,038	34,038
R-squared	0.909	0.910

Notes: The dependent variable is the logarithm of transaction price per m^2. Housing characteristics and controls at the district level are included in all specifications. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Standard errors in the parentheses are clustered at the community × year-month level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B6: Robustness tests for alternative cluster levels

lnPrice	(1) Cluster at district × year-month	(2) Cluster at city × year-month	(3) Cluster at community × quarter	(4) Cluster at district × quarter	(5) Cluster at city × quarter
Dis_inciner	0.0138***	0.0138***	0.0138***	0.0138***	0.0138***
	(0.0022)	(0.0022)	(0.0024)	(0.0026)	(0.0026)
Post	-0.0215	-0.0215*	-0.0215	-0.0215	-0.0215
	(0.0252)	(0.0127)	(0.0276)	(0.0264)	(0.0148)
Dis_inciner × Post	-0.0042***	-0.0042**	-0.0042**	-0.0042**	-0.0042**
	(0.0016)	(0.0018)	(0.0020)	(0.0018)	(0.0021)
Control variables	X	X	X	X	X
Business-district FE	X	X	X	X	X
Month-by-year FE	X	X	X	X	X
City-year-month FE	X	X	X	X	X
Constant	-15.6224**	-15.6224**	-15.6224	-15.6224*	-15.6224
	(6.5585)	(7.7471)	(10.1771)	(8.3275)	(9.8380)
Observations	34,038	34,038	34,038	34,038	34,038
R-squared	0.914	0.914	0.914	0.914	0.914

Notes: The dependent variable is the logarithm of transaction price per m^2. Housing characteristics and controls at the district level are included in all specifications. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Standard errors in the parentheses are clustered at the district × year-month level, city × year-month level, community × quarter level, district × quarter level, and city × quarter level in columns 1-5, respectively. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B7: Robustness to omitted variable bias

Variable	(1) lnPrice
Dis_inciner × Post	-0.00417***
	(0.0018)
Bound on the treatment effect	(-1.22679, -0.00417)
($\delta = 1,\ R_{\max} = 1.3 \times R^2$)	
Treatment effect excludes 0	Yes
$\delta \left(R_{\max} = 1.3 \times R^2\right)$	-0.05603

Appendix C Selection process for the plants that are ideal for the fifth robustness test

Considering that the Ministry of Ecology and Environment approved *Management Regulations on the Application of Automatic Monitoring Data of Domestic WtE incineration Plants* on October 11, 2019, calling for the implementation of the regulations from January 1, 2020, we limit samples to those that were put into operation before January 2020 to avoid any potential noise caused by this external shock. 15 plants were put into operation from post-CIEN to January 2020. Moreover, given that it takes around a year for CIEN to exert its impact on the housing price gradient (Fig. 1), we set the start of our sample period at October 2018. Following the same matching process in Section 4.2, we finally obtain 1,031 transaction data within 10 km of 5 WtE incineration plants. Table C1 presents the names of these plants, the cities where they are located and the dates on which they were put into operation.

Table C1: Locations and operation commencement dates of the WtE incineration plants

City	WtE incineration plant	Commencement date of operation
Hangzhou	Everbright Environmental Energy (Hangzhou) Co., Ltd.	November 26, 2017
Dalian	Hanlan (Dalian) Solid Waste Treatment Co., Ltd.	June 29, 2018
Tianjin	Tianjin Taihuan Recycling Resources Co., Ltd.	September 7, 2019
Qingdao	Qingdao West Coast Kangheng Environmental Protection Energy Co., Ltd.	September 8, 2019
Beijing	Beijing Huayuan Huizhong Environmental Protection Technology Co.,Ltd.	November 15, 2019

Appendix D Definition of the *Access* variable

In this section we elaborate on the assignment rules for the *Access* variable. When the community is located within 1 km of the plant, the variable equals 3. When the community is located within 2 km of the plant, the variable equals 2. When the following three requirements are all met, the variable equals 1: (1) the community is located between 2 km and 3 km from the plant; (2) there is a bus line between the community and the plant; (3) the bus stops of departure and destination are within 1 km of the community and the plant, respectively (see Fig. D1).

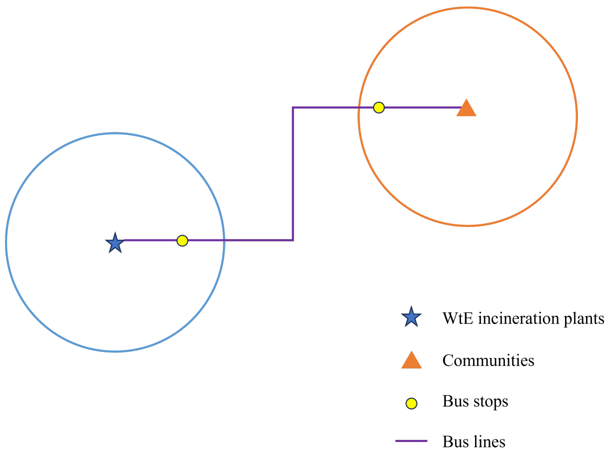

Fig. D1: Illustration of the situation when *Access* equals 1.
Notes: The distances between the WtE incineration plants and the communities are 2-3 kilometers.

Appendix E Illustration of downwind and non-downwind communities

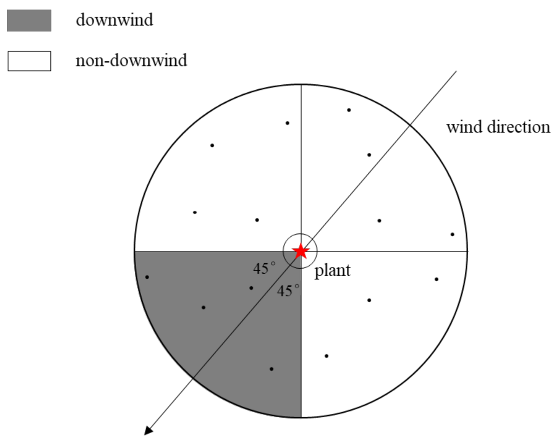

Fig. E1: Definition of downwind and non-downwind communities.
Notes: Definitions of downwind and non-downwind communities within 10 km of the plant are illustrated using northeastern wind as an example.

Appendix F Heterogeneity of treatment effects

Table F1: Heterogeneity across WtE incineration plants

lnPrice	(1) Urban area	(2) Plant age	(3) Treatment capacity	(4) Flue gas abatement control ability
Dis_inciner	0.0136***	0.0150***	0.0144***	0.0143***
	(0.0020)	(0.0021)	(0.0020)	(0.0020)
Post	-0.0271	-0.0159	-0.0258	-0.0142
	(0.0266)	(0.0270)	(0.0267)	(0.0269)
Dis_inciner × Post	-0.0021	-0.0034*	-0.0056***	-0.0054***
	(0.0018)	(0.0017)	(0.0018)	(0.0018)
Dis_inciner × Post × Urban	-0.0036***			
	(0.0012)			
Dis_inciner × Post × Age		-0.0030**		
		(0.0015)		
Dis_inciner × Post × High Capacity			0.0028**	
			(0.0012)	
Dis_inciner × Post × Ranking				0.0062**
				(0.0026)
Control variables	X	X	X	X
Business-district FE	X	X	X	X
Month-by-year FE	X	X	X	X
City-year-month FE	X	X	X	X
Constant	-12.6662	-14.7059*	-14.8202*	-14.5229*
	(8.8540)	(8.6946)	(8.6388)	(8.7327)
Observations	34,038	34,038	34,038	34,038
R-squared	0.914	0.914	0.914	0.914

Notes: The dependent variable is the logarithm of transaction price per m^2. Housing characteristics and controls at the district level are included in all specifications. Transaction price and housing area are winsorized at the 1st and 99th percentiles. Standard errors in the parentheses are clustered at the community × year-month level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix G Definition of the *Ranking* variable

In this section we present the definition of the *Ranking* variable. On January 1, 2020, the online monitoring data of flue gas emissions from WtE incineration plants was fully released to the public on the Ministry of Ecology and Environment's public platform for automatic monitoring data of domestic WtE incineration plants.[19] Using these public data, the waste incineration ESG big data research team consisting of Qingqi Group, Shanghai Qingyue, and Wuhu Ecology Center collected 1,989,468 daily average flue gas data from more than 500 plants in operation nationwide, covering five indicators, including sulfur dioxide, nitrogen oxides, particulate matter, hydrogen chloride, and carbon monoxide. Based on the annual average value and emission stability of the five indicators for each plant, the research team finally formed the ranking of 504 plants' flue gas abatement control abilities in 2020 following the principle of 'ow pollutant emissions and high emission stability. Accordingly, we generate a dummy variable *Ranking*, which equals 1 when the ability of the plant is ranked more than 252.

[19]Website: https://ljgk.envsc.cn.