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ARTICLE

Economic effects of air quality on housing prices: evidence from Beijing, China

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Abstract
Air pollution is a major environmental urban issue, particularly in fast-growing cities in developing countries. Reducing air pollution is thus a challenge while evaluating the economic value of air quality is crucial for environmental policies made. However, few studies accurately estimate this value as they neglect the possible endogeneity issues, as well as the dynamic and heterogeneous effects of air pollution. Under the hedonic framework, we therefore assess the economic effect of fine particulate matter ($PM_{2.5}$) on housing prices in Beijing, China. We construct a panel based on resale apartment transactions matched with average quarterly $PM_{2.5}$ data between 2013 and 2019. To reduce the risk of an estimation bias, we apply an instrumental variable (IV) approach. Our results show that $PM_{2.5}$ is negatively associated with housing prices. Households were willing to pay an extra 0.0852% per housing unit price for an average quarterly reduction in $PM_{2.5}$ of 1 μg/m^3. Furthermore, we argue that high-income dwellers tend to pay more for clean air. The negative effects of $PM_{2.5}$ across regions are significant and different. Compared with that in the basic year 2013, the negative effect increases in the first 3 years and then decreases in the last 3 years. Our findings enhance our comprehension of the economic impact of air quality and make a valuable contribution to the nuanced understanding of willingness to pay for air quality, which is beneficial in assessing and optimizing environmental regulations.

Keywords Air pollution · Hedonic price · Instrumental variables · Heterogeneous effects · Dynamic impact · Willingness to pay

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1 Introduction

Air pollution has provoked wide concern as it threatens human health (Landrigan et al., 2018) and hinders economic development (Dominici et al., 2014; He et al., 2016; Lichter et al., 2017). Considerable efforts have been made to reduce air pollution, especially in fast-growing urban metropolises, such as Beijing, China. Since air is considered a common good and its pollution is a negative externality to other activities (e.g., labor productivity), it is difficult to judge who should be charged for pollution and what the price should be (Chang et al., 2019; Klingen & van Ommeren, 2020; Liu et al., 2020; Schulze et al., 1981). It is therefore important to have accurate estimates of the economic value of air quality as a key input for cost–benefit analyses of cleaner air and pollution regulation strategies for policymakers (Chay & Greenstone, 2005; Freeman III, 1974).

To date, several studies have estimated the economic value of air quality improvement on housing prices based on various approaches, such as hedonic price modelling and the avoidance behavior approach (Hitaj et al., 2018; Liu et al., 2018). In these, hedonic price models are used as a cost–benefit framework to estimate the benefits of air quality based on its causal impacts on housing prices. This strategy has been adopted widely in order to assess the value of environmental goods including air quality, noise and other pollutants (Anderson Jr & Crocker, 1971; Baranzini et al., 2010; Zabel & Guignet, 2012). Hedonic pricing enables us to capture the effect of air quality more accurately and objectively under stable, long-run yet dynamic conditions and further permits the assessment of residents' marginal willingness to pay (MWTP) for clean air (Bednarz, 1977; Palmquist, 2005). The latter is important to devise efficient policy strategies to improve air quality.

The economic value of air quality as measured using a hedonic price model, has been researched in various developed countries, both across and within cities (Bajari et al., 2012; Hitaj et al., 2018; McCord et al., 2018; Won Kim et al., 2003). Recently, reducing air pollution has also gained a high priority in emerging and developing countries (Shiva Nagendra et al., 2021), particularly because industrialization accompanied by rapid urbanization has worsened air quality there (Ebenstein et al., 2015; Greenstone & Hanna, 2014). Although the body of literature focusing on the inter-city or regional level for developing countries, is increasing (Chen & Jin, 2019; Freeman et al., 2019; Zou, 2019), evidence at the within-city level is largely lacking, mainly due to data constraints.

This lack of within-city evidence in developing countries constitutes a methodological challenge and enhances the problems created by omitted variable bias. First, the standard hedonic price model based on cross-sectional data typically results in biased estimates because housing attributes (both time-variant and time-invariant) that are correlated with air quality are easily overlooked, and the dynamic effects of air quality over time cannot be captured as well. Second, despite the fact that a panel analysis could correct for the effect of time-invariant variables with the help of fixed effects, endogeneity issues from correlated time-varying variables still exist (Chay & Greenstone, 2005). Third, if there is heterogeneity across individuals in their preferences for clean air, then individuals may self-select into locations on the basis of these unobserved differences. In short, removing the bias from omitted variables is a crucial step to obtaining accurate estimated results.

To bridge these knowledge gaps, we took Beijing, the capital of China, as a case to assess the economic value of air quality within the city by applying a hedonic price framework. With an instrumental variable (IV) approach, we assessed the influence of air pollution on housing prices by adopting resale transaction data on residential apartments over the period 2013–2019, a period of worsening air pollution across China (Tilt, 2019).

Further, we tested the possible heterogeneous effects across regions and income levels and dynamic effects over time.

Our study contributes to literature in three ways. First, using quarterly air pollution data and econometric strategies, we provide a more accurate assessment of the effect of air pollution on housing prices at an intra-urban level. Our quarterly panel data avoid the bias caused by cross-sectional data, and our use of fixed effects accounts for possible seasonal effects. Also, by adopting an instrumental variable (IV) approach, we address possible endogeneity issues, namely that air pollution is likely to be correlated with unobserved characteristics, allowing us to examine causal associations (Sullivan, 2016). Second, our research design allows us to explore heterogeneous responses to air pollution for households across regions and income groups. Considering the possible heterogeneous effects (Chen et al., 2018; Le Boennec & Salladarré, 2017), the analysis refines the effects of air pollution, and mitigates the risk of estimation bias as well. Lastly, we capture the dynamic change in air quality possibly affecting housing prices over time. Such a setting contributes to a better understanding of how housing prices respond to the change in air quality which may reflect the awareness of residents to air pollution (Lang, 2015).

2 Literature review

2.1 Estimation methods for the economic value of air quality

The literature on the economic value of air pollution is mostly concerned with estimating individuals' marginal willingness to pay (MWTP) for clean air through behavioral changes. Three approaches have been put forward (Baranzini & Ramirez, 2006).

First, the "avoidance/defensive cost" approach assesses individuals' MWTP by their defensive expenditures for avoiding the consequences of pollution—for example, through wearing face masks or using air purifiers (Ito & Zhang, 2020; Zhang & Mu, 2018). Nevertheless, such behavior is likely to lead to combined influences. Even if avoidance costs are expected to be lower than the costs of possible damages, people would pay to avoid those damages. Thus, using defensive expenditures as a proxy for welfare changes seems problematic when estimating the MWTP for air quality improvement.

Second, the "cognitive preference" adopts contingent valuation methods (CVMs), conjoint analysis surveys, or choice experiments based on individuals' subjective perceptions. For instance, Dong and Zeng (2018) used CVMs to gauge the public MWTP for haze mitigation in Beijing. They found that respondents were willing to pay 0.55–0.82% of their annual income to avoid smog. Strong underlying assumptions are that respondents are familiar with their personal preferences and that people's true willingness to pay is stated objectively and accurately. Since these assumptions are possibly not fulfilled, the willingness to pay for air quality improvement calculated by CVM is possibly biased.

Third, the hedonic pricing approach is frequently applied to determine the economic value of air quality based on its effect on housing prices, in which a non-market good such as air quality can in fact be traded in the housing markets (Freeman, 1981; Palmquist, 2005). In this assumption, residents prefer to live in locations with cleaner air because they want to minimize the possible health hazards caused by air pollution, and more so as environmental consciousness increases. Of course, housing with better air quality has a higher price. As a result, residents make a trade-off between higher housing prices and clean air. Through this technique, residents' MWTP to air quality improvement can be calculated.

The standard hedonic price model, when applied during the housing market valuation process, may also suffer from estimation bias. In cross-sectional data, the issue of endogeneity is often overlooked (Chen et al., 2018). In panel data, endogeneity arises from the fact that local economic activities are associated with air quality and housing prices, which may lead to a reduction in the accuracy of estimates (Chen & Jin, 2019). Furthermore, there may be heterogeneous effects across income groups, making it difficult to obtain an accurate explanation of the value of air quality from average estimates.

To overcome these issues, we adopted an instrumental variables (IV) approach with panel data to estimate the dynamic effect of air quality over time and its heterogeneity effect across regions and income groups. This approach allowed us to address the issue of endogeneity and minimize estimation bias, thereby providing more accurate estimates of the economic value of air quality.

2.2 Housing prices and air pollution under a hedonic pricing approach

Recent studies in developed countries that applied hedonic models reported a negative association between housing prices and air pollutants. Most other studies at the within-city level focused on US or European cities. Taking the St. Louis Metropolitan Area of (U.S.) as a study area, Nourse (1967) presented the first empirical estimates of air quality affecting housing prices. Bayer et al. (2009) found a greater MWTP for clean air in multiple US metro regions. McCord et al. (2018) used 2013–2018 housing sales in the UK to assess the implicit price of air pollution. However, due to contextual differences, it is problematic to transfer Western findings to developing countries (He et al., 2016).

As environmental conditions worsened in many developing countries, studies at an inter-urban level gained momentum. For instance, Chen and Jin (2019) examined inverse air pollution effects on housing prices in China's 286 cities in 2005–2013, while Freeman et al. (2019) added regional migration costs to a residential sorting model to more accurately estimate the economic value of air quality in China for 2005. Both studies concluded that Chinese residents are willing to pay extra for clean air. Given that high migration costs do not apply to residents moving within a city, the mechanisms, and the willingness to pay to evade air pollution differ between the inter-urban and the intra-urban level.

Studies at the intra-urban level were mainly based on cross-sectional data. For instance, using data from Shanghai in 2010, Chen et al. (2018) found adverse effects of air pollution on urban housing prices: reducing concentrations of sulfur dioxide (SO_2) and PM_{10} by 1 mg/m^3 increased Shanghai's housing prices, on average, by 0.6% and 0.9% respectively (or 159 yuan/m^2 and 238 yuan/m^2). Based on the installation and operation of an air-purifying tower in the city of Xi'an, Lan et al. (2020) adopted a quasi-experimental design, namely a difference-in-difference approach, to measure the tower's ability to mitigate haze, and found that it increased housing prices by, on average, 4% across the affected area. He & Collins (2020) and Mei et al. (2020) found negative air pollution effects on housing prices across the metropolises of Guangzhou and Beijing through panel data. However, neither study took into account that dynamic and heterogeneity effects of air pollution with long time series are possible and that results may vary across different subgroups (He & Collins, 2020; Mei et al., 2020), likely biasing the estimated economic value of clean air. These shortcomings are addressed in our study.

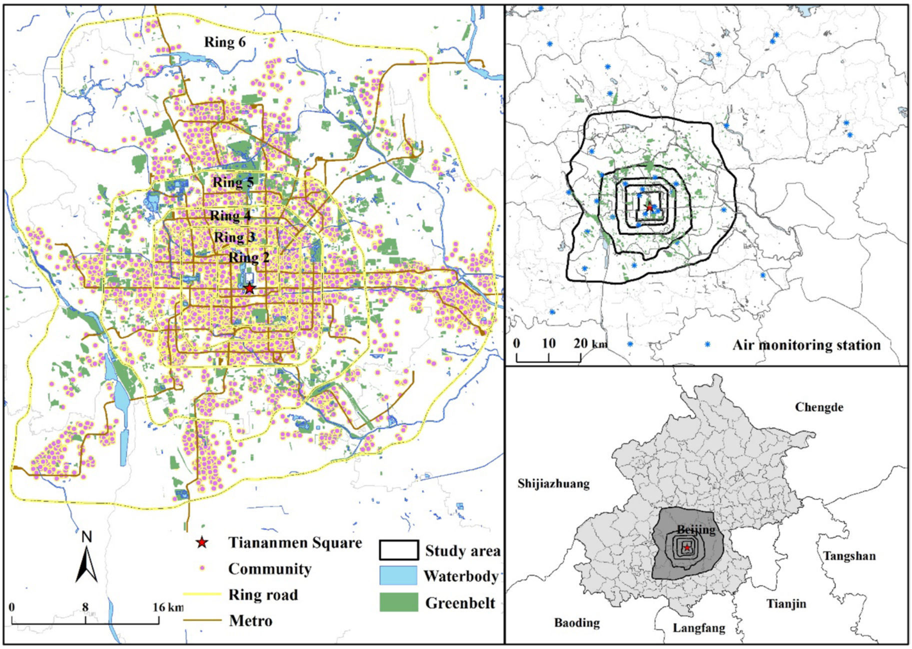

Fig. 1 The metropolitan area of Beijing

3 Materials and methods

3.1 Study area

Beijing is China's capital and political center. The incomes and living standards of its 21.54 million residents are higher than those of people in other parts of the country. Because the northern part of China suffers from more severe air pollution than the south (Xu et al., 2019), its residents are likely to care more about their neighborhood environment (Aunan & Wang, 2014). Therefore, Beijing represents an ideal case to explore the economic effect of clean air on housing prices.

Our study focused on the area within Beijing's 6th ring road, as this encompasses the main urban areas (Fig. 1). The city's ring roads have been designed to relieve central parts from the traffic induced by urban sprawl. Beijing's six ring roads, which are centered on Tiananmen Square, enclose mainly residential areas, and divide the city into different functional areas (see Table 7 in the Appendix) (Gao et al., 2016). The population within the 3rd–6th ring roads accounts for 57% of Beijing's total population (Beijing Statistical Publishing, 2019). Although a polycentric structure is slowly emerging in Beijing (Qin & Han, 2013), housing prices still gradually decline with increasing distance from the inner to the outer ring.

3.2 Data

3.2.1 Housing data

Housing transactions between 2013 and 2019 on the existing stock were collected through web scraping from the Lianjia[1] platform. The sample of 395,040 observations gathered excludes public housing programs, single detached dwellings, and government-subsidized housing. The data concerns only resale transactions, as opposed to newly built homes, as resales are more likely to reflect true market prices (Li et al., 2019). Per housing unit, we also obtained several structural characteristics including, for example, area, floor, orientation, and longitude and latitude (Table 1).

Based on these housing transactions, we calculated the average prices of each community (i.e., residential quarter or unit consisting of many buildings with housing) and the average quarterly housing price within each ring road over time. Figure 2 shows the distribution of the average price over the city, obtained by means of ordinary kriging interpolation. The map indicates that housing prices roughly decline with increasing distance to the urban center. Figure 3, moreover, shows the average quarterly housing prices within each ring road. While the average quarterly housing price increased over time until 2017, a decrease is noticeable thereafter. The price within the inner ring is always higher than within the outer ring, which confirms the observations of Yang and Shen (2008).

In a first-stage regression, we obtained predicted unit prices in logarithms for each community in each quarter, using as explanatory variables the apartment area, the square of that area, floor, orientation, number of bedrooms, decoration, building style, and the presence of an elevator. Table 2 provides descriptive statistics per variable at housing and community levels. Since not all communities had continuous observations throughout the period, our final dataset forms a random sample out of the total possible universe of 7051 communities' times 24 quarters. It is a panel dataset of 2794 communities (with 33,538 housing units) that are observed from the 4th quarter of 2013 to the 4th quarter of 2019.

3.2.2 Neighborhood data

We obtained data on public service amenities (e.g., schools and hospitals) and the population density at the community level (i.e., housing blocks). Amenities for each sample year from 2013 to 2019 were gathered based on the points of interest extracted from Amap (https://www.amap.com/). Their addresses were geocoded, with an accuracy of 100%. A population density raster surface with a spatial resolution of 1 km was obtained from WorldPop (https://www.worldpop.org/).

In hedonic price theory (Rosen, 1974), not only housing structural attributes, accessibility (i.e., location) and neighbourhood quality are key influences on housing prices. Thus, for each community, we determined the street distance to the nearest city centre/subcenter (i.e., Tiananmen Square, Jianguomen central business district (CBD), Beijing Financial Street, the technology hub of Zhongguancun Science Park, and the Olympic Park) (Qin & Han, 2013), and to the nearest school, hospital, city park, shopping mall, farmers' market, bus stops and metro stations. We also determined for each separate year the number of

[1] Lianjia is the largest real estate trading platform in China, covering the sale of new and pre-owned housing sales, and a realtor and housing renovation business (https://bj.lianjia.com/).

Table 1 Description of the variables

Category	Variable	Definition
Housing price	Housing price	Unit price per apartment (yuan/m^2)
Structural attributes	House age	Dummy variable: Age of house divided into decades: Age1 (1950–1979), Age2 (1980–1989), Age3 (1990–1999), Age4 (2000–2009), Age5 (2010–2019)
	Floor area	Floor area (m^2)
	Bedroom number	Number of bedrooms
	Building style	Dummy variable (1 = slab-type building; 0 = otherwise)
	Orientation	Dummy variable (1 = apartments with southern orientation; 0 = otherwise)
	Elevator	Dummy variable (1 = apartment with an elevator; 0 = otherwise)
	Decoration	Dummy variable (Dec1 = apartments with refined decoration, Dec2 = with simple decoration, Dec3 = with roughcast)
	Floor level	Dummy variable (Floor1 = top, Floor2 = high, Floor3 = middle, Floor4 = low, Floor5 = ground)
Locational accessibility	D_CBD	Distance to the nearest urban center/subcenter (Tiananmen Square, Jianguomen CBD, Beijing Financial Street (BFS), Zhongguancun Science Park (ZSP, the technology hub), Olympic Park) (m)
	D_Bus stop	Distance to the nearest bus stop (m)
	D_Metro station	Distance to the nearest metro station (m)
Neighborhood characteristics	School	Distance to the nearest school (kindergarten, primary, middle school) (m)
	Hospital	Distance to the nearest hospital ("triple A" and comprehensive hospitals) (m)
	Park	Distance to the nearest city park (m)
	Shopping mall	Distance to the nearest shopping mall (m)
	Famers' market	Distance to the nearest famers' market (m)
	Basic services	Number of basic services (e.g., restaurant, barber shop, post office, parcel delivery, laundry) within 1 km
	Leisure facilities	Number of sport and leisure facilities (e.g., karaoke, bar, museum, gym) within 1 km
	Population	Population density per community (people/km^2)
Air pollution	$PM_{2.5}$	Quarterly concentrations of average $PM_{2.5}$ (μg/m^3)
Thermal inversion	Strength	The temperature difference in altitudes of 110 and 330 m within each 1-h period, and then averaged for each period. Taking Positive difference as strength, while negative one sets zero. (°C)
	Number of inversions	Quarter days with thermal inversions (days)

basic services (e.g., post office, laundry) and leisure facilities (e.g., museum, gym) within 1000 m (Table 1).[2]

3.2.3 Air pollution and meteorological data

We extracted air pollution data at 35 fixed monitoring stations (Fig. 1) as hourly measurements collected from the Beijing Municipal Environmental Monitoring Center (http://www.bjmemc.com.cn/). We calculated quarterly averages of particulate matter with an aerodynamic diameter of < 2.5 μm, commonly called $PM_{2.5}$. $PM_{2.5}$ is a mixture of solid particles and liquid droplets in the air, which causes smog or hazy conditions. The air pollution in Beijing is caused by not only local emissions (Zhang et al., 2016) but also the spillover of pollution from neighboring cities, such as Tianjin, Langfang, and Tangshan (Yue et al., 2019) (Fig. 1). Reducing $PM_{2.5}$ concentrations is a mandatory target in the "Air Pollution Prevention Action Plan" for the Beijing–Tianjin–Hebei region (Zhang & Mu, 2018).

For robustness checks, we also obtained the quarterly averages of China's ambient air quality index (AQI) alongside $PM_{2.5}$. The AQI is a composite measure comprising six pollutants, namely sulfur dioxide (SO_2), carbon monoxide (CO), nitrogen dioxide (NO_2), PM_{10}, ozone (O_3), and $PM_{2.5}$. We interpolated these variables across the study area on a 20 × 20 m grid using ordinary kriging (Anselin & Le Gallo, 2006; Kuntz & Helbich, 2014).

A dataset on thermal inversions was obtained from the Climate Data Store (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=overview). We used the gridded ERA5, which divides the earth by 0.25° × 0.25° (approximately 25 km × 25 km), and records the 1-h air temperature at 37 layers, ranging from 1000 to 1 hPa. Within each 1-h period, we calculated the temperature difference between the second layer (975 hPa) and the first layer (1000 hPa). A positive difference refers to a thermal inversion. The difference measures the inversion strength. We coded a negative difference as zero. We then averaged the inversion strength across all 1-h lapses within each 1-quarter period.

3.3 Model specifications

3.3.1 Model at the housing level

To assemble panel data at the community level, we fitted an ordinary least squares (OLS) regression model at the housing level to estimate the value per community price with fixed quarter and community effects:

$$\ln HP_{ijt} = \beta + \alpha S_{ijt} + \ln CP_{jt} + \theta_t + \xi_{ijt} \tag{1}$$

where $\ln HP_{ij_0t}$ is the logged transaction unit price of apartment i in residential community j in quarter t, t belongs to the time range from the 4th quarter of 2013 (2013:Q4) to the 4th quarter of 2019 (2019:Q4). Note that 2017:Q4, 2018:Q3, and 2018:Q4 were excluded due to missing data in these periods.S_{ij_0t} is a vector of structural features of apartment i in community j and quarter t, α are the coefficients, $lnCP_{jt}$ is the logged price of residential

[2] A distance threshold of 1000 m was chosen because it corresponds with 15-min' walking distance, which is frequently used in community planning.

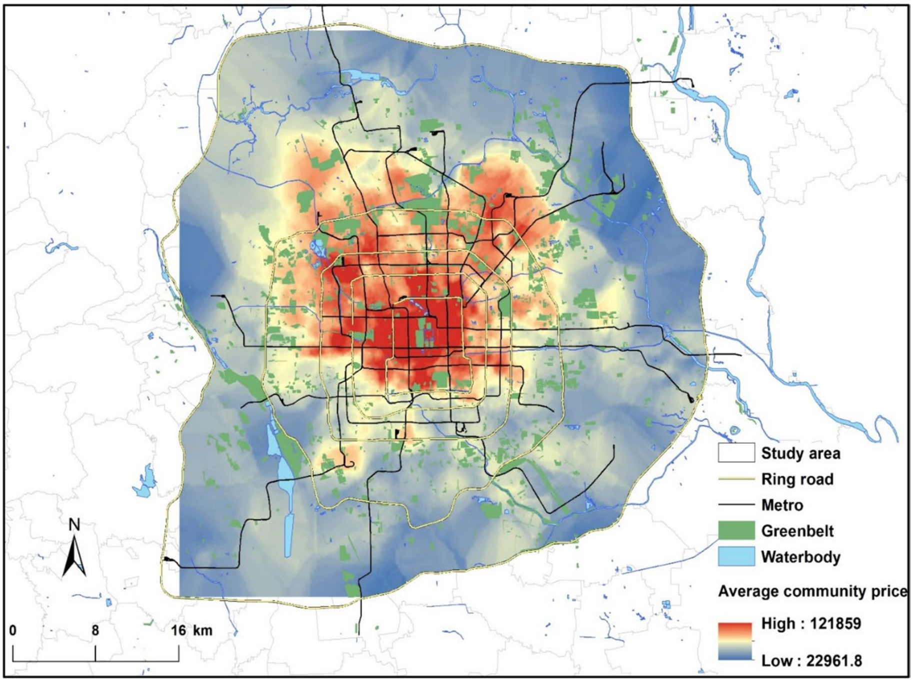

Fig. 2 Distribution of average community prices based on pooled data

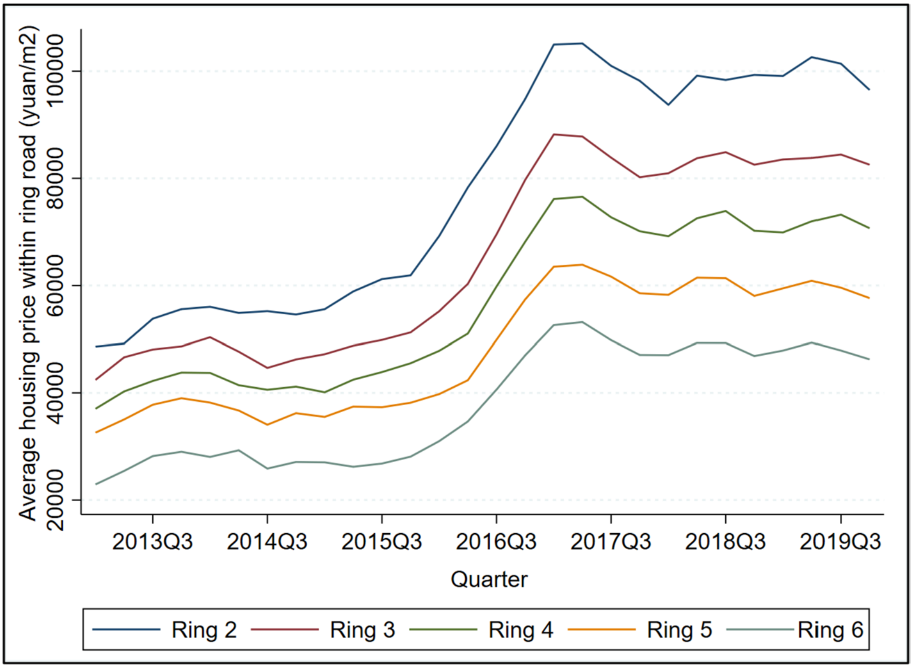

Fig. 3 Average housing price within each ring road over time

Table 2 Descriptive statistics

Variable	Mean	Std. dev	Min	Max	Variable	Mean	Std. dev	Min	Max
Housing units (N = 333,269)									
Housing price	10.82	0.440	1.099	11.92	Age5	0.104	0.305	0	1
Floor area	79.97	34.94	9.640	640	Floor1	0.113	0.316	0	1
Bedroom number	2.000	0.760	0	9	Floor2	0.221	0.415	0	1
Building style	0.264	0.441	0	1	Floor3	0.379	0.485	0	1
Orientation	0.295	0.456	0	1	Floor4	0.204	0.403	0	1
Elevator	1.941	0.739	0	8	Floor5	0.0812	0.273	0	1
Age1	0.615	0.487	0	1	Dec1	0.449	0.497	0	1
Age2	0.148	0.356	0	1	Dec2	0.341	0.474	0	1
Age3	0.279	0.449	0	1	Dec3	0.0197	0.139	0	1
Age4	0.448	0.497	0	1					
Community units (N = 33,538)									
Community price	0.0291	0.423	− 5.104	1.285	Shopping mall	6.953	0.799	0.733	9.278
$PM_{2.5}$	122.396	43.011	47.322	272.47	Farmer's market	6.467	0.983	0.0123	9.031
D_CBD	8.917	0.771	5.869	10.49	Basic services	4.867	1.005	0	6.950
D_Bus stop	6.028	0.921	0.0949	8.689	Leisure facilities	3.984	0.970	0	6.392
D_Metro station	7.066	0.772	0.371	9.418	Population	9.580	0.933	5.418	11.73
School	5.806	1.076	0.0319	8.514	Strength	1.058	0.369	0.073	1.915
Hospital	6.651	0.874	0.0138	8.867	Number of inversions	3.665	0.689	0	4.369
Park	6.742	0.807	0.143	8.872					

community j *in quarter t*. θ_t is to control the quarter effect and ξ_{ij_0t} is the error term. The regression results for this first stage are shown in Table 8 of the Appendix.

3.3.2 OLS model at the community level

To test the influence of air pollution on housing prices, we first specified a benchmark model (i.e., pooled OLS model) using a semi-log specification at the community level:

$$\ln CP_j = \beta + \gamma \ln A_j + \chi \ln N_j + \kappa PM_{2.5j} + \varepsilon_j \tag{2}$$

where $lnCP_j$ is the logged price of residential community j. $A_{j,}$ $N_{j,}$ and $PM_{2.5j}$ refer to the accessibility, neighborhood variables, and $PM_{2.5}$ at the community level. β is the constant, γ, χ, and κ are the estimated coefficients, and ε_j is an error term.

3.3.3 Fixed effects model

To eliminate the correlation between unobserved factors and $PM_{2.5}$ and to obtain an unbiased estimate of the implicit price of air quality, we then proceed to a fixed effects model (FE), with time and individual dummies (a so-called two-way FE specification)[3]:

$$FE: \ln CP_{jt} = \beta + \gamma \ln A_{jt} + \chi \ln N_{jt} + \kappa PM_{2.5jt} + \theta_y + \mu_j + \varepsilon_{jt} \tag{3}$$

where a year-fixed effect θ_y controls for time-varying economic shocks (e.g., policy changes in the housing market) and a community-fixed effect μ_j controls for time-invariant characteristics across communities.

3.3.4 Fixed effects two-stage least squares (FE2sls) model

Endogeneity remains an issue under the FE (or random effects model) specification if time-varying unobserved factors affect both air pollution and housing prices (Bajari et al., 2012). To ensure more accurate estimates compared to the OLS model, we calculate the relationship between the estimated prices and air pollution by instrumenting $PM_{2.5}$ with the logarithm of the number of inversions and that of inversion strength. Other studies confirmed that such thermal inversion partly reduces air pollutants (Chen et al., 2022). These two IVs satisfy the basic conditions, namely instrument relevance (i.e., corr $(Z, X) \neq 0$) and instrument exogeneity (i.e., corr $(Z, \varepsilon) = 0$), where X is the endogenous variable $PM_{2.5}$ and ε is the random perturbed variable. Our first-stage IV equation is:

$$PM_{2.5jt} = \beta + v_1 \ln tinum_{jt} + v_2 \ln tistr_{jt} + \gamma \ln A'_{jt} + \chi \ln N'_{jt} + \theta_y + \mu_j + \varepsilon_{jt} \tag{4}$$

and the second-stage IV equation is:

$$\ln CP_{jt} = v + \gamma \ln A''_{jt} + \chi \ln N''_{jt} + kPM_{2.5jt} + \theta_y + \mu_j + w_{jt} \tag{5}$$

where $PM_{2.5jt}$ is the predicted ambient $PM_{2.5}$ concentration in community j in quarter t. The other variables and coefficients are similar to those in Eq. (3).

[3] The Hausman test was significant ($p = 0.00$), indicating that the fixed effects model fits better than a random effects model.

3.3.5 Dynamic effects

To assess whether and how residents' MWTP for air quality improvement changes over time, we further explored the dynamic effects of air pollution on housing prices by adding $PM_{2.5} \times$ year interaction terms:

$$\ln CP_{jt} = \beta + \gamma \ln A_{jt} + \chi \ln N_{jt} + k_0 PM_{2.5jt} + k_y \left(PM_{2.5jt} \times Year_y \right) + \theta_y + \mu_j + \varepsilon_{jt} \quad (6)$$

where the year 2013 is set as the base period, and the dummy variable $Year_y$ equals 1 in the year y and 0 otherwise, giving us separate values of k_y for 2014–2019, which show the change in the effect of air pollution on housing prices compared with the base period 2013.

4 Results and discussion

4.1 Benchmark regression results

Table 3 reports the results of pooled OLS, two-way FE, and FE2SLS regressions. Given that the variance inflation factors (VIF) of the independent variables reached a maximum of 1.08—which is far below the critical value of 10—multicollinearity was not an issue in our models. Estimated coefficients for $PM_{2.5}$ were, as expected, negative and significant at least at the 5% level, showing that pronounced $PM_{2.5}$ levels are likely to reduce housing prices across three models. Among them, The IV estimates were larger due to relieving the endogeneity, compared with the FE estimates and the OLS estimates.

In the IV regression, the results of the F-statistic exceeded 10 in the first stage, indicating that the IVs were suitably correlated with the endogenous variable. The Sargan test statistic was significant ($p = 0.0058$), indicating that overidentification for the IVs is not an issue. The effect of $PM_{2.5}$ according to the IV estimation implied that a 1 μg/m^3 increase in $PM_{2.5}$ concentration causes a 0.0852% reduction in the housing unit price. This decrease was smaller compared with findings reported for other major Chinese cities, including in earlier cross-sectional studies in Qingdao (Chen & Chen, 2012), Shanghai (Chen et al., 2018), and Beijing (Mei et al., 2020). This difference is probably related to our stronger analysis design (i.e., cross-sectional vs. panel data, annual vs. quarterly panel data), but could also be attributed to environmental improvements in Beijing.

Some estimates for the control variables (e.g., accessibility and neighborhood characteristics) were significant in the OLS but not in FE and FE2sls models; their signs were, however, in line with expectations and largely consistent with earlier studies (Qin & Han, 2013; Yuan et al., 2018). Since the distance to the nearest urban center/subcenter for each community point does not change over time, coefficients for D_CBD were not estimated in the FE and FE2sls models. Based on the FE2sls results, none of the additional control variables (except for distance to the nearest bus stop) displayed a statistically significant marginal covariation with housing prices during the period of study. This may be because of correlations with the estimated prices at the community level or other confounding factors.

4.2 Robustness check

To evaluate the robustness of our result for $PM_{2.5}$, we re-estimated the OLS, FE, and FE2sls models with the AQI as an alternative proxy for air pollution. Again, the coefficients were negative and statistically significant (Table 9 in the Appendix). Except for the FE model, the signs and magnitudes of AQI coefficients were in keeping with those of $PM_{2.5}$ in corresponding models. These results imply that our estimates for $PM_{2.5}$ were robust. Besides, to examine the potential measurement errors caused by the spatial variation of air pollution, we extracted the subsample of housing communities which are within 3 km of the air stations to test the effect of air pollution. The estimate coefficients of $PM_{2.5}$ and AQI are significantly negative, confirming the robustness of our models (Table 10 of the Appendix).

4.3 Effects of $PM_{2.5}$ across income levels

Moreover, following the empirical work of Chen et al. (2018) and Cai and Gao (2022), we conducted a quantile regression with IVs to explore the possible heterogeneous effects of air quality impact on housing prices across different income levels by dividing houses in our sample into quartiles (low, middle-low, middle-high, and high). Table 4 shows the estimated coefficients of $PM_{2.5}$ with other variables being controlled. The significantly negative coefficients for housing prices in Q25 (−0.0141), Q50 (−0.0151), Q75 (−0.0168), and Q90 (−0.0189) indicate that housing prices would be discounted by air quality with more significant discounts observed in higher-priced housing group. That is, dwellers purchasing higher-priced houses care more about air quality, which is consistent with the findings of Chen et al. (2018) for Shanghai.

4.4 Effects of $PM_{2.5}$ across regions

Further, we tested the heterogeneous effects of $PM_{2.5}$ across regions. Thus, we ran stratified analyses based on ring roads 2–6. The estimation results for $PM_{2.5}$ across ring roads using FE2sls regressions are shown in Table 5. The $PM_{2.5}$ estimates for all rings are significant and negative at the 1% level, thus confirming the negative influence of $PM_{2.5}$ on housing prices across regions within ring roads. However, the magnitude of the estimates gradually decreases with increasing distance from the core city: a 1 $\mu g/m^3$ increase in $PM_{2.5}$ leads to an average reduction in the housing price of 0.1113% and 0.0867% within rings 2–3, and 0.1037%, 0.0774%, and 0.0622% within rings 4–6. It can be seen that the coefficients of $PM_{2.5}$ within each ring road are significantly different. However, the estimates are not statistically significant when we compare their difference (see Fig. 4 in the Appendix). This suggests that we cannot compare the magnitudes of the estimated coefficients for the ring roads statistically.

4.5 Dynamic effects

Taking 2013 as a baseline, the differences in the estimated $PM_{2.5}$ effect between per year (2014–2019) and 2013 are presented in Table 6. The Chow test statistic testing their joint

Table 3 Regression results

	(1) OLS	(2) FE	(4) FE2sls
$PM_{2.5}$	−0.000740***	−0.000104***	−0.000852***
	(0.0000564)	(0.0000183)	(0.0000489)
School	0.00109	−0.000500	−0.000619
	(0.00152)	(0.000621)	(0.000639)
Hospital	0.00259	0.00000956	−0.0000938
	(0.00193)	(0.00149)	(0.00153)
Park	−0.00214	−0.000844	−0.000768
	(0.00207)	(0.00128)	(0.00132)
Shopping mall	0.00255	−0.000897	−0.000798
	(0.00236)	(0.00117)	(0.00120)
Farmer's market	0.000310	0.000366	0.000478
	(0.00185)	(0.000826)	(0.000850)
Leisure facilities	0.0113***	−0.00154*	−0.00136
	(0.00195)	(0.000812)	(0.000834)
Basic services	0.00384**	0.000859	0.000895
	(0.00185)	(0.000733)	(0.000753)
Population	0.190***	−0.00397	−0.00410
	(0.00186)	(0.00439)	(0.00452)
D_Bus stop	0.00146	−0.00187*	−0.00200*
	(0.00195)	(0.00108)	(0.00111)
D_Metro station	0.00111	−0.000214	−0.000120
	(0.00239)	(0.00229)	(0.00235)
D_CBD	−0.0162***	0	0
	(0.00241)	(.)	(.)
Constant	−1.873***	0.300***	0.364***
	(0.0410)	(0.0491)	(0.0506)
Community effect	#	Yes	Yes
Year-fixed effect	Yes	Yes	Yes
N	33,538	33,538	33,538
Adjusted R^2	0.458	0.839	0.830

Heteroskedasticity-robust standard errors clustered at the community level. Standard errors in parentheses. Significance levels in all tables: $^{*}p<0.1$, $^{**}p<0.05$, $^{***}p<0.01$

difference showed that the coefficients of $PM_{2.5}$ are significantly different over time, excluding between 2018 and 2019 (Table 11 in the Appendix). The coefficient for 2013 was −0.00232 and statistically significant at the 1% level. Compared with 2013, the estimated coefficient decreased by −0.00329 in 2014, by −0.00341 in 2015, and by −0.00217 in 2016, indicating that the negative effect of $PM_{2.5}$ intensified over time. However, the estimated coefficient increased by 0.00078 in 2016, 0.000134 in 2017, and 0.00014 in 2019 (insignificant), relative to 2013, implying the $PM_{2.5}$ negative effects reduced slightly over the last 3 years.

Table 4 Heterogeneous effects: results of quantile regression with IVs

	Q25	Q50	Q75	Q90
$PM_{2.5}$	−0.0141***	−0.0151***	−0.0168***	−0.0189***
	(0.00039)	(0.00033)	(0.00028)	(0.00031)

Table 5 Heterogeneous effects: estimators based on the ring roads (FE2sls)

	Ring2	Ring3	Ring4	Ring5	Ring6
$PM_{2.5}$	−0.00111***	−0.000867***	−0.00104***	−0.000774***	−0.000622***
	(0.000176)	(0.0000932)	(0.000106)	(0.000124)	(0.0000809)

Our results suggest that $PM_{2.5}$ had a stronger influence on housing prices after the severe smog in 2013 (Mei et al., 2020), but that recently the effect has weakened to a minor extent. This may be due to air quality improvements across Beijing over time as a result of various environmental policies, such as the Clean Air Action Plan 2013–2017 (Zhang et al., 2016). In 2017, the concentration was <60 μg/m^3 and met the targets outlined in Beijing's Clean Air Action Plan 2013–2017.

5 Conclusions

Considering the endogeneity issues and potential heterogeneity effect across space–time, this study provides more precise and comprehensive evidence of the value of air quality on housing prices by taking thermal inversions as IVs. By using resale transaction prices of residential apartments in Beijing from 2013 to 2019, we evaluate the economic effect of air quality ($PM_{2.5}$) as a whole and how its effects vary across regions, income groups, and over time.

In keeping with most previous studies in both developed and developing countries (Chasco & Le Gallo, 2015; Hitaj et al., 2018; Tian et al., 2017), our results of Beijing confirm that $PM_{2.5}$ is negatively associated with housing prices. We found that households are willing to pay 0.0852% of the housing unit price for a reduction of 1 μg/m^3 in $PM_{2.5}$ concentrations. This result indicates that the MWTP in Beijing is relatively moderate compared to that in developed countries (Bajari et al., 2012), and in other major Chinese cities such as Shanghai and Qingdao (Chen et al., 2018; Chen & Chen, 2012).

Quantile regression with IVs showed the heterogenous effects of $PM_{2.5}$ across income levels, high-income households are willing to pay more for clean air than low-income groups, echoing the results of prior studies (Chen et al., 2018). It seems that the rich care more about the health risks attributed to air pollution and thus tend to pay extra for good air quality, while monetary costs exclude the poor from this amenity since they have to spend their money on fixed costs and living essentials (Dong & Zeng, 2018). Based on our findings, it seems reasonable to tax high-income households to a larger degree when air pollution funds are set up. Policymakers should be aware that supporting households with low incomes might be a way to compensate for their lost welfare as a result of the spatial inequality of air quality in the city. Besides, spatially stratified models showed that

Table 6 Changes in the $PM_{2.5}$ estimates compared with 2013

Year	2013 (Baseline)	2014	2015	2016	2017	2018	2019
$PM_{2.5}$	− 0.00232***	− 0.00329***	− 0.00341***	− 0.00217***	0.000780***	0.000134**	0.000140**
	(0.000041)	(0.000039)	(0.000041)	(0.00005)	(0.000048)	(0.00006)	(0.000071)

the significantly negative influence of $PM_{2.5}$ is different across ring roads. In this case, environmental regulation should account for these regional differences rather than a 'one size in all' approach.

Finally, we examined whether the $PM_{2.5}$ effect varies temporally relative to the year 2013. We found that the negative impact gradually increased in 2014 and 2015; in 2016 it also increased but to a minor extent compared to the first 2 years. This could mean that the public became increasingly aware of health-threatening impacts owing to exposure to air pollutants in 2013. However, relative to 2013, the effect in 2017, 2018 and 2019 decreases. However, the difference did not reach statistical significance between 2018 and 2019. On the whole, the negative effect mainly declined in the last 3 years. This decline may be associated with pollution control actions like the Clean Air Action Plan 2013–2017. In fact, the measured concentration levels of $PM_{2.5}$ in 2017 and 2019 met the targets of that action plan (Zhang et al., 2016). Hence, the dynamic effects also implicitly provide evidence for the effectiveness of Beijing's environmental regulation actions. Further research is needed to determine whether it is the current reduction in pollution or future government commitments to improve air quality that impact the current willingness to pay.

Our study had several limitations that must be considered when interpreting our findings. First, we incorporated only average quarterly $PM_{2.5}$ concentrations as a proxy for air pollution rather than daily measurements. Though indirectly considered in our sensitivity tests with the AQI, we cannot exclude those other pollutants (e.g., SO_2, NO_2, PM_{10}) that may affect housing prices differently. More pollutant indicators could be considered in future work. Second, air pollutant data stemmed from a restricted number of official monitoring stations that are unevenly distributed across space. While our air pollution data facilitated the incorporation of spatiotemporal trends in $PM_{2.5}$, small-scale variations are likely to have been unrecognized. Whether and, if so, to what extent this limitation affected our estimates needs to be addressed in the future using high-resolution air pollution data. Finally, because we used a hedonic model specification, we only indirectly evaluated the willingness to pay for clean air based on the housing market conditions, without obtaining people's perceptions directly. Future research is advised to combine subjective and objective measures to comprehensively explore the effect of air pollution.

Appendix

See Fig. 4 and Tables 7, 8, 9, 10 and 11.

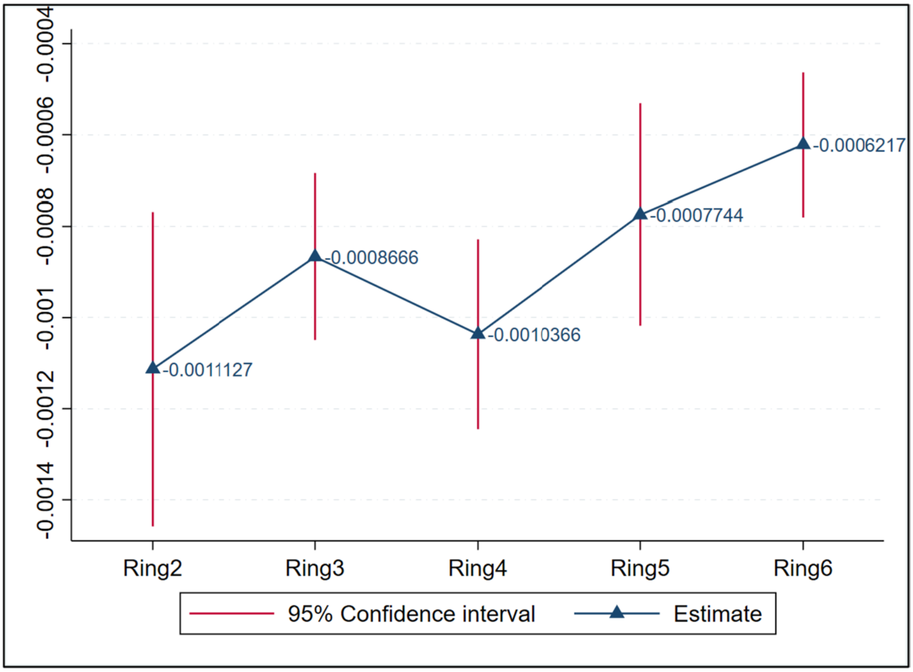

Fig. 4 Comparation between the regression coefficients of $PM_{2.5}$ across ring roads

Table 7 Overview of areas within each of Beijing's ring roads

Ring road	Construction period	Areas connected	Functions of the area inside each ring
Ring #1	1920s–1950s	Boundary does not exist anymore; Tiananmen, Forbidden City, and Di'an men	Historical areas
Ring #2	1980s–1990s	Dongcheng Qu (Eastern Urban Precinct), Xicheng Qu (Western Urban Precinct), Xuanwu Precinct and Chongwen Precinct	Old city
Ring #3	1980s–1990s	Beijing's CBD (Guandongdian) and diplomatic communities (Dongzhimenwai/Liangmaqiao, Jianguomenwai)	Central business district (CBD), as well as an important residential area for the local population
Ring #4	Completed in 2001	Connects the Zhongguancun technology hub, western Beijing, the Fengtai District, and eastern Beijing	Economic development zones, but also an important residential area for the local population
Ring #5	Completed in 2003	Located approximately 10 km from central Beijing, and links the suburban areas of Huantie, Shigezhuang, Dingfuzhuang, etc. Also passes through the Beijing Development Area	Residential area for immigrant population
Ring #6	2001–09	Shunyi District, Tongzhou District, Changping District, and Daxing District	Suburban districts

Table 8 Regression results of housing prices in the first stage

Variables	Coefficients	Variables	Coefficients
Floor area	−0.00179***	Floor1	−0.0324***
	(0.0000294)		(0.00853)
Age1	#	Floor2	0.00618
	#		(0.00849)
Age2	0.0431***	Floor3	0.0110
	(0.00245)		(0.00849)
Age3	0.0492***	Floor4	0.00149
	(0.00269)		(0.00852)
Age4	0.0631***	Floor5	0.0131
	(0.00306)		(0.00861)
Age2	0.0336***	Bedroom number	0.0207***
	(0.00445)		(0.000884)
Elevator	−0.0210***	Orientation	0.0220***
	(0.00132)		(0.000616)
Dec1	0.0214***	Constant	10.86***
	(0.00112)		(0.00897)
Dec2	−0.00185		
	(0.00113)		
Dec3	−0.0157***		
	(0.00185)		
Community effect		Yes	
Quarter-fixed effect		Yes	
N		333,269	
Adjusted R^2		0.925	

Heteroskedasticity-robust standard errors clustered at community level, and standard errors in parentheses. Significance levels: $*p<0.1$, $**p<0.05$, $***p<0.01$

Table 9 Robustness check for air quality: Regression estimates for AQI

	(1) OLS	(2) FE	(3) FE2sls
AQI	−0.000415***	−0.000184***	−0.00117***
	(0.0000661)	(0.0000221)	(0.0000779)
School	0.00111	−0.000475	−0.000552
	(0.00152)	(0.000621)	(0.000659)
Hospital	0.00262	0.0000264	−0.000113
	(0.00193)	(0.00149)	(0.00158)
Park	−0.00224	−0.000873	−0.000770
	(0.00208)	(0.00128)	(0.00136)
Shopping mall	0.00244	−0.000918	−0.000873
	(0.00237)	(0.00117)	(0.00124)
Farmer's market	0.000272	0.000334	0.000444
	(0.00185)	(0.000825)	(0.000877)
Leisure facilities	0.0112***	−0.00157*	−0.00145*
	(0.00196)	(0.000811)	(0.000860)
Basic services	0.00372**	0.000822	0.000985
	(0.00185)	(0.000732)	(0.000776)
Population	0.191***	−0.00392	−0.00387
	(0.00187)	(0.00439)	(0.00466)
D_Bus stop	0.00143	−0.00182*	−0.00196*
	(0.00196)	(0.00108)	(0.00114)
D_Metro station	0.00106	−0.000220	−0.000283
	(0.00240)	(0.00229)	(0.00242)
D_CBD	−0.0162***	0	0
	(0.00241)	(.)	(.)
Constant	−1.956***	0.268***	0.435***
	(0.0410)	(0.0491)	(0.0528)
Community effect	Yes	Yes	Yes
Year-Fixed effect	Yes	Yes	Yes
N	33,538	33,538	33,538
R^2	0.455	0.839	0.819

Heteroskedasticity-robust standard errors clustered at community level, and standard errors in parentheses. Significance levels: *$p<0.1$, **$p<0.05$, ***$p<0.01$

Table 10 Robustness check for air quality: Regression estimates for subsample within 3 km distance from any air monitoring station

	(1) OLS	(2) FE	(3) FE2sls	(4)
$PM_{2.5}$	−0.000717***	−0.0000975***	−0.000832***	
	(0.0000853)	(0.0000257)	(0.0000729)	
AQI				−0.00117***
				(0.000114)
School	−0.00165	−0.00180**	−0.00175*	−0.00172*
	(0.00230)	(0.000885)	(0.000911)	(0.000939)
Hospital	0.00256	−0.000151	−0.0000701	0.0000255
	(0.00286)	(0.00229)	(0.00236)	(0.00243)
Park	−0.00305	−0.000518	−0.000300	−0.000374
	(0.00289)	(0.00170)	(0.00175)	(0.00180)
Shopping mall	−0.00260	−0.00185	−0.00171	−0.00181
	(0.00355)	(0.00163)	(0.00168)	(0.00173)
Farmer's market	−0.00509*	−0.000803	−0.000657	−0.000750
	(0.00267)	(0.00115)	(0.00119)	(0.00123)
Leisure facilities	0.00914***	−0.00170	−0.00172	−0.00174
	(0.00299)	(0.00119)	(0.00123)	(0.00127)
Basic services	0.0141***	0.00156	0.00134	0.00149
	(0.00280)	(0.00107)	(0.00110)	(0.00113)
Population	0.233***	0.00111	0.0000220	0.00131
	(0.00326)	(0.00624)	(0.00642)	(0.00662)
D_Bus stop	−0.00194	−0.00205	−0.00243	−0.00232
	(0.00301)	(0.00154)	(0.00158)	(0.00163)
D_Metro station	0.0333***	−0.000692	−0.000271	−0.000280
	(0.00361)	(0.00311)	(0.00319)	(0.00329)
D_CBD	−0.0287***	0	0	0
	(0.00362)	(.)	(.)	(.)
Constant	−2.276***	0.370***	0.439***	0.504***
	(0.0633)	(0.0706)	(0.0729)	(0.0761)
Community effect	Yes	Yes	Yes	Yes
Year-fixed effect	Yes	Yes	Yes	Yes
N	15,656	15,656	15,656	15,656
R^2	0.450	0.852	0.843	0.833

Standard errors in parentheses Significance levels: $*p<0.1$, $**p<0.05$, $***p<0.01$

Table 11 Chow test for the joint difference in the results of dynamic effect of $PM_{2.5}$

Chow-test	$2013PM_{2.5}$	$2014PM_{2.5}$	$2015PM_{2.5}$	$2016PM_{2.5}$	$2017PM_{2.5}$	$2018PM_{2.5}$	$2019PM_{2.5}$
$2013PM_{2.5}$							
$2014PM_{2.5}$	968.49***						
$2015PM_{2.5}$	1258.95***	31.96***					
$2016PM_{2.5}$	16.51***	1802.54***	3459.31***				
$2017PM_{2.5}$	7371.72***	21,697.31***	36,889.20***	18,740.29***			
$2018PM_{2.5}$	3010.20***	8652.71***	13,240.83***	7152.10***	568.12***		
$2019PM_{2.5}$	2290.72***	6245.21***	8576.02***	4934.82***	352.83***	0.04	–

Significance levels: *$p<0.1$, **$p<0.05$, ***$p<0.01$

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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