Impacts of air pollution on urban housing prices in China

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Received: 9 June 2020 / Accepted: 19 April 2021 / Published online: 10 June 2021
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Abstract
In this study, we examine pollution effects on urban housing prices in China, using a fixed effects 2SLS model on a 13-year (2005–2017) panel dataset of 237 prefecture-level cities. We find that urban housing prices are negatively associated with PM$_{2.5}$ levels, presenting an elasticity of −0.32 for the entire sample. In large cities with an urban population of ≥ 5 million, the elasticity further increases in absolute value to −0.34, reflecting greater marginal benefit associated with a unit percentage PM$_{2.5}$ reduction in a higher pollution band. In addition, PM$_{2.5}$'s effects on housing markets present temporal variations, and the base elasticity of −0.29 for earlier periods increases to −0.33 in the post-2008 period, reflecting increased public awareness of pollution-caused health risk after the Beijing Olympic Games. In the post-2014 period, however, the elasticity declines to −0.24 with stricter pollution regulations introduced in late 2013 as part of the 12th Five Year Plan. Rational expectations regarding continued air-quality improvement in the future may underlie this trend.

Keywords Hedonic price model · Air pollution · China · Housing markets · Elasticity · Environmental regulations

JEL Classification C36 · Q53 · R31

1 Introduction
China’s rapid industrialization and urbanization have increased demand for energy on a massive scale, and its high dependence on coal in its energy supply has caused severe environmental degradation—most notably, air pollution (Kahn & Zheng, 2016; World Bank and DRC, 2014). Among conventional air pollutants, particulate matter (PM) is known to cause the most serious damage to human health, and thus has received particular public attention (Bickel & Friedrich, 2005; Burnett et al., 2014; Matus et al., 2012; OECD, 2016).
Once inhaled, fine particulate matter—often measured as PM$_{10}$ (PM with a diameter of ≤10 μm) or PM$_{2.5}$ (PM with a diameter of ≤ 2.5 μm)—harms human respiratory and circulatory systems, leading to morbidities and mortalities associated with cardiopulmonary diseases (Lighty et al., 2000). Historic PM levels in China have been excessively high. In 2015, for example, PM$_{2.5}$ levels in 31 major cities exceeded the World Health Organization (WHO) alert levels by a factor of ≤8 (Nam, 2021).

In this context, pollution impact studies have received increased attention in the policy circle, and played a critical role in raising public awareness of the need for air-quality control. Numerous impact studies, for example, estimate that welfare loss from excess PM pollution in China reaches 3.1–9.9% of China’s historic gross domestic product (GDP) levels (Nam et al., 2019a; World Bank & IHME, 2016; Zhang et al., 2017). The results warn that pollution-induced socioeconomic costs in China are too large to ignore, requiring imminent public actions for pollution abatement. This message has been taken seriously among policy makers, leading to a gradual change in their “economy over environment” mentality. China’s current air-quality standards and pollution abatement targets, increasingly tightened throughout the 12th and 13th Five Year Plan (FYP12/13) period (2011–2020), reflect this change, with visible air-quality improvement outcomes (Song et al., 2017).

Despite their critical role in policy arena, one aspect of the impact studies often criticized is the uncertainty involved in their central estimates. Various data and methodological issues may underlie this uncertainty, and one of them is the varied willingness-to-pay (WTP) estimates used for long-term effects valuation (Nam et al., 2019b; Viscusi & Aldy, 2003). Long-term exposure to excess PM leads those with normal health conditions to premature deaths, and associated labor and leisure loss accounts for over half the PM-caused welfare damage (World Bank & IHME, 2016). Translating premature mortality cases into dollar terms requires WTP estimates (i.e., how much each individual is willing to pay to avoid a given health risk), which are often based on contingent valuation (stated preference). The survey-based estimates, however, present large variations by sample, region, and time, and could even be affected by the questionnaire design itself (Hammitt & Zou, 2006; Hoffmann et al., 2017).

An alternative to contingent valuation is to use direct market data and apply a revealed preference model. A key assumption underlying this approach is that market prices of a certain good, such as a real estate property, already reflect a premium on quality amenities (e.g., clean air) although they themselves do not carry explicit prices (Din et al., 2001). In other words, WTP for air-quality improvement may be measured indirectly by examining how real estate markets respond to air quality, and hedonic models have been widely used for this purpose (Anderson & Crocker, 1971; Chay & Greenstone, 2005). Despite its sole focus on market impacts, the hedonic literature is a good complement to the contingent-valuation literature, as it could reduce the subjectivity inherent in WTP surveys.

In China’s context, the hedonic literature on pollution costs is still sparse, despite the need for reliable WTP estimates for impact studies. So far, we have identified only seven studies on this topic, published in major peer-reviewed journals, and found some critical limitations in each study. Of the seven studies, for example, two (Zheng & Kahn, 2008; Zheng et al., 2010) adopt a conventional one-step ordinary least squares (OLS) approach, subject to potential estimation bias, and the single-year cross-sectional studies by Huang & Lanz (2018) and Freeman et al. (2019) do not incorporate potential time trends. Of the remaining three panel studies based on a two-stage least squares (2SLS) approach, Zheng et al. (2014) focus on PM$_{10}$, whose weaker association with human health makes their estimates less relevant to the recent PM$_{2.5}$-focused pollution impact literature (Cohen et al., 2017). More recent PM$_{2.5}$-focused panel studies by Chen & Chen (2017) and Chen & Jin

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(2019) seemingly address the methodological issues mentioned above, but the robustness of their central results on earlier periods requires further empirical evidence and an extension of the time dimension to the post-2013 period, when stringent pollution regulations were implemented nationwide. Our study is motivated to fill this gap.

In this study, we apply a 2SLS hedonic price model to a 13-year (2005–2017) panel dataset of 237 Chinese prefecture-level cities, focusing on particulate matter, which accounts for over 90% of the welfare damage associated with air pollution in China (Matus et al., 2012; Nam et al., 2019a). Our main goal is twofold. One is to enrich the empirical literature on WTP estimates for pollution impact assessment, which in particular applies 2SLS to city panels on PM$_{2.5}$. The other is to test how such WTP estimates change over time and how they interact with recent public interventions aiming at pollution abatement.

2 Hedonic price models for air quality valuation

How can clean air be valuated? Air quality valuation is essential when policy makers conduct cost–benefit analysis in planning and evaluating pollution regulations (Mendelsohn & Olmstead, 2009). However, such valuation is challenging, as clean air is not a market good carrying an explicit price. One of the most popular approaches is to use the human body as a receptor of differing air quality (Brajer & Mead, 2004; Cohen et al., 2017; Matus et al., 2008; Nam et al., 2019a; Nielsen & Ho, 2007; Vennemo et al., 2006). Exposure to excess pollution increases health risk, and the medical expenditure and wage/leisure loss associated with pollution-induced morbidities and mortalities can capture part of the socio-economic costs of air pollution (Nam et al., 2010).

Another method commonly applied to air quality valuation is hedonic price modelling, where housing price is treated as a function of various property and location-specific characteristics. The logic underlying this approach is that air quality is implicitly capitalized to the market price of housing (Ridker & Henning, 1967). Earlier studies estimate such price effects of pollution using conventional cross-sectional hedonic models or comparable fixed-effects specification in panel data settings, but their findings tend to diverge (Rosen, 1974). A group of studies find that air pollution is negatively associated with housing prices as assumed, although in some cases the identified negative correlations lack statistical significance (e.g., Atkinson & Crocker, 1987; Brucato et al., 1990; Smith & Huang, 1995). However, there are also studies that fail to find any significant correlations (e.g., Li & Brown, 1980; McDonald, 1985) or find mixed evidence or even a positive pollution-price feedback loop against reasonable market behavior (e.g., Berry, 1976).

The inconsistent hedonic estimation results in the earlier literature are partly due to methodological limitations embedded in the “conventional” hedonic approach. For example, unobservable market characteristics reflected in the error terms may be correlated with property prices, and neglecting this possibility, which is often the case, could lead to biased estimation results (Chay & Greenstone, 2005). This omitted variable bias can be avoided with a fixed effects model specification in a panel data setting. Also, a conventional one-step OLS model specification is subject to potential endogeneity, as a certain economic shock having positive effects on household incomes and energy consumption can affect both air pollution and housing price at the same time (Zheng et al., 2014). For this reason, more recent hedonic studies take a 2SLS approach with fixed effects terms and instruments for air pollution instead of directly conducting one-step OLS estimation. Overall,
SLS-based results tend to be consistent (e.g., Bayer et al., 2009; Chay & Greenstone, 2005; Zheng et al., 2014). In China’s context, the 2SLS-based hedonic literature is limited, but empirical evidence exists in support of negative pollution-price correlations (Table 1). Three of the four studies focusing on PM\(_{10}\) are cross-city analyses, and present an elasticity of −0.74 to −0.35. Among them, two 2SLS-based studies (Huang & Lanz, 2018; Zheng et al., 2014) show very close results (elasticities of −0.71 and −0.74), which posit much stronger marginal WTP (MWTP) than the OLS estimate by Zheng et al. (2010) (elasticity of −0.35). The downward bias in MWTP, found in the latter, is potentially associated with the omitted variable bias or endogeneity problem latent in one-step OLS application in hedonic regression (Chay & Greenstone, 2005). Two recent PM\(_{2.5}\)-focused panel studies (Chen & Chen, 2017; Chen & Jin, 2019) arrive at consistent elasticity estimates (−0.43 to −0.21). However, a more robust conclusion would require further scientific testing within an identical methodological framework.

### 3 Methodology

#### 3.1 2SLS regression and model specification

In this study, we take a 2SLS approach to avoid potential endogeneity and omitted-variable bias, to which a conventional one-step hedonic model is subject. Our central hypothesis is that overall housing market prices in each city reflect the amenities from local air quality, as well as a set of local socioeconomic conditions having direct effects on market demand and price, such as population, local wage levels, and industry mix. This hypothesis is built on two conceptual lenses. One is that cross-city variations in location-specific amenities are adjusted through housing prices and wages, as is assumed in a typical spatial equilibrium model (Brueckner, 2011). The other is that the value of non-market goods is reflected

| Sample | Method | Years studied | Pollutant | Elasticity* | MWTP** (RMB/ m\(^2\)) |
|--------|--------|---------------|-----------|-------------|------------------------|
| Chen & Chen (2017) | 286 prefecture-level cities | 2SLS | 2004–2013 | PM\(_{2.5}\) | [−0.43, −0.21] | 46 |
| Chen & Jin (2019) | 286 prefecture-level cities | 2SLS | 2005–2013 | PM\(_{2.5}\) | −0.24 | 12 |
| Huang & Lanz (2018) | 288 prefecture-level cities | 2SLS | 2011 | PM\(_{10}\) | −0.71 | 38 |
| Zheng & Kahn (2008) | 900 housing units in Beijing | OLS | 2004–2005 | PM\(_{10}\) | −0.87 | 30 |
| Zheng et al. (2010) | 35 prefecture-level cities | OLS | 1997–2006 | PM\(_{10}\) | −0.35 | 10 |
| Zheng et al. (2014) | 85 prefecture-level cities | 2SLS | 2006–2009 | PM\(_{10}\) | −0.74 | 28 |

*PM elasticity of housing price, defined as \((\Delta y/y)/(\Delta x/x)\) where \(x\) and \(y\) are PM levels and housing price, respectively.

**Unit housing price change per unit (1 µg/m\(^3\)) increase in PM concentrations.
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in other related market goods, as is posited by revealed preference theory (Rosen, 1974). We test our main hypothesis with a 2SLS model, and examine whether PM$_{2.5}$ levels (as a treatment variable measuring local air quality) offer a significant explanatory power for city-level urban housing prices even when city-specific socioeconomic characteristics are controlled for. In the first stage, we determine control and instrumental variables (IVs) on PM$_{2.5}$ levels and estimate pollution regression models. We then incorporate estimated PM$_{2.5}$ levels with the first-stage regression into our main hedonic price model.

Our first-stage regression model is given in Eq. 1, where $x_{it}$ is PM$_{2.5}$ levels in city $i$ at time $t$; $Z_{i,t-1}$ and $D_{it}$ are matrices of city-level attributes and cross-boundary pollution controls, respectively; $\pi_1$, and $\pi_2$ are vectors of parameters to be estimated; $a_i$ and $\eta_i$ are city-fixed effects and year-fixed effects terms, respectively; $C$ is a constant; and $\nu_i$ is an error term.

$$x_{it} = Z_{i,t-1} \pi_1 + D_{it} \pi_2 + a_i + \eta_i + C + \nu_i$$ (1)

Variables included in $Z_{i,t-1}$ are population (POP), annual mean wage per worker (WAG) and share of manufacturing employment (MFG) (Table 2). These variables are closely associated with the degree of anthropogenic PM pollution, and are at the same time key determinants of urban housing prices. Accordingly, those included in $Z$ are also used as right-hand side (RHS) variables for second-stage regression. A one-year time lag is set between $Z$ and $x$ to clarify the direction of causality and thus control for potential endogeneity.

In contrast, $D_{it}$ contains three IVs, which explain local PM levels without direct contribution to local housing prices. Two of them are climate variables with codirectional effects on $x$ in China’s context: annual mean precipitation (PRE) causing wet scavenging effects is negatively associated with local PM levels (Guo et al., 2016; Pu et al., 2011); annual mean temperature (TEMP) can serve as a good predictor of anthropogenic PM pollution, given that cooling and heating demand during hot and cold seasons is a primary determinant of local energy consumption patterns in China (Deschênes & Greenstone, 2011). The third IV is transboundary pollution (TP), measured as inverse distance-weighted PM$_{2.5}$ concentrations in nearby upwind regions.

In detail, transboundary pollution measurement for city $i$ at time $t$ ($TP_{it}$) is constructed as shown in Eq. 2, where $w_{ij}$ is a weight given as a fraction of the year city $i$ and nearby city $j$ within its downwind area are aligned to a monthly dominant wind direction; $x_{jt}$ is annual mean PM$_{2.5}$ level in $j$ at $t$; and $d_{ij}$ is physical distance between $i$ and $j$ measured in kilometers (km).

$$TP_{it} = \sum_{j \in J} \frac{w_{ij} \cdot x_{jt}}{\left(\max\left(\frac{d_{ij}}{100}, 1\right)\right)^2}$$ (2)

Weight term $w_{ij}$ is based on the official station-specific time series wind direction data published by the National Centers for Environmental Information (NCEI, 2020). The data covers nationwide 415 monitoring stations in total, and records either hourly or trihoral dominant wind directions in 10-degree intervals. We aggregate the original 36 directions (from 10° to 360°) into four common directions and compute the relative frequency of each direction for a given year to determine the weight (Fig. 1). In constructing TP, a set of nearby cities $j$ consisting of upwind region $J$ is limited to those located within a 500 km radius from city $i$ with reference to Freeman et al. (2019). TP is a valid IV, given that wind direction is strictly exogenous to socioeconomic attributes, and air pollution in upwind cities is largely independent of the local housing price in a given city.
| Variable Definition | Obs | Mean   | Std. Dev |
|---------------------|-----|--------|----------|
| **Variables of Interest** |     |        |          |
| Housing Price ($y$) | 3081 | 4.09E+03 | 2.98E+03 |
| PM$_{2.5}$ ($x$) | 3081 | 5.29E+01 | 18.3E+01 |
| **City Attribute Covariates ($Z$)** |     |        |          |
| Population ($POP$) | 3081 | 1.45E+02 | 1.92E+02 |
| Wage ($WAG$) | 3081 | 3.86E+04 | 1.52E+04 |
| Manufacturing Share ($MFG$) | 3081 | 4.22E−01 | 1.42E−01 |
| **City and Time Dummies** |     |        |          |
| Large City 1 ($BIG1$) | 3081 | 4.35E−02 | 2.04E−01 |
| Large City 2 ($BIG2$) | 3081 | 4.25E−01 | 4.94E−01 |
| Post-2008 ($T1$) | 3081 | 6.92E−01 | 4.62E−01 |
| Post-2014 ($T2$) | 3081 | 2.31E−01 | 4.21E−01 |
| **Instrumental Variables ($D$)** |     |        |          |
| Transboundary Pollution ($TP$) | 3081 | 2.13E+02 | 1.41E+02 |
| Precipitation ($PRE$) | 3081 | 9.85E+02 | 5.88E+02 |
| Temperature ($TEMP$) | 3081 | 5.79E+01 | 1.02E+01 |
Once the first-stage model is estimated, its predicted values ($\hat{x}_{it}$) is used as a RHS variable in our main cross-city hedonic model. The second-stage model is shown in Eq. 3, where $y_{it}$ is housing price in $i$ at $t$; $\beta$ and $\gamma$ are a parameter and vectors of parameters to be estimated, respectively; $\mu_i$ and $\lambda_t$ are city-fixed effects and year-fixed effects terms, respectively; and $\epsilon_{it}$ is an error term. All other notations in the equation are identical to those in Eq. 1.

Control variables included in $Z_{i,t-1}$ are as defined for Eq. 1. First, POP is a proxy for aggregate urban housing demand, which is a key determinant of housing prices. Second, WAG reflects the level of human capital or public amenities, which likely imposes substantial premiums on housing prices (Rauch, 1993). Third, MFG approximates the level of industrialization and thus demand for labor, positively associated with housing demand (Zheng et al., 2014). In China’s context, migrant workers—often invisible in official demographic statistics—have functioned as a primary source of urban labor supply, suggesting that relative manufacturing performance may complement POP in estimating actual housing demand (Nam, 2017).

One point to be noted in our 2SLS approach is that both first-stage and second-stage equations include the identical covariate matrix $Z$. This is to express $y_{it}$ as a linear combination of controls ($Z$) and instruments ($D$). That is, plugging Eq. 1 into Eq. 3 transforms our original second-stage equation into Eq. 4, where $\varphi_1$ and $\varphi_2$ are column vectors of parameters.

$$y_{it} = \beta \hat{x}_{it} + Z_{i,t-1}' \gamma + \mu_i + \lambda_t + C + \epsilon_{it}$$

(3)

$$y_{it} = Z_{i,t-1}' \varphi_1 + D_{i,t}' \varphi_2 + \mu_i + \lambda_t + C + \epsilon_{it}$$

(4)

Then, an unbiased estimate for $\beta$ can be obtained through $\varphi_2 \odot \pi_2$—a Hadamard division of the second-stage coefficient vector for $D$ by the corresponding first-stage coefficient vector.
In addition to our central estimates based on Eq. 3, we also test several temporal and geographic controls in the form of interaction terms, hypothesizing that certain time- and location-specific characteristics may affect the PM elasticity. For this purpose, we additionally include in the model vector $T_i$ which contains the interaction terms between time period or city-size dummies and $x$ (Eq. 5).

$$y_{it} = \beta x_{it} + Z'_{i,t-1} \gamma_1 + T_i' \gamma_2 + \mu_i + \lambda_t + C + \epsilon_{it}$$ (5)

On the one hand, two city-size dummies are used to test potential size-biased market premiums. Population thresholds of 5 million (BIG1) and 1 million (BIG2) are used to split large cities into two tiers. On the other hand, two time dummies—post-2008 ($T_1$) and post-2014 ($T_2$)—are used to test the potential market impacts associated with increased public awareness of PM-induced health risk and with rational expectation based on growing stringency of anti-pollution measures. The 2008 Beijing Olympic Games offered key momentum for publicizing the need for pollution abatement and introducing elevated anti-pollution measures in major cities (Kahn & Zheng, 2016). A detailed action plan on air pollution prevention and control, prepared for Chinese major urban areas as part of the 12th Five Year Plan (2011–2015), adds another layer by imposing stringent air-quality control targets and signaling the state’s continued efforts on cleaner air (Nam, 2021; State Council, 2013). This action plan was announced in September 2013, and we set 2014 as the threshold for $T_2$, considering the time lag needed for its observable implementation effects.

### 3.2 Data

Our 13-year panel dataset for 237 Chinese prefecture-level cities is built from various public and commercial sources (see Fig. 2 for the spatial distribution of the 237 cities and the Appendix for the full list of cities). Annual mean PM$_{2.5}$ levels in each city (2005–2017) are computed from the 36″×36″ PM$_{2.5}$ concentration grids for China (V4.CH.02) developed by van Donkelaar et al. (2019) and the 60″×60″ LandScan population grids (Oak Ridge National Laboratory, 2019). Those PM$_{2.5}$ grid cells within each city’s administrative boundary are overlaid with the population grids to estimate population-weighted PM$_{2.5}$ levels, and these population-weighted annual means are used for this study. Socioeconomic variables, including housing price and climate IVs, are constructed from multiple published sources, including China’s official national and local statistical yearbooks, NCEI (2020), and CEIC Data (2020). We measure housing price in terms of the average sales price of a newly-built commodity housing stock with inflation adjustment (in constant 2015 prices), following the literature (e.g., Chen & Chen, 2017; Chen & Jin, 2019; Zheng et al., 2014). Basic descriptive statistics for all variables are provided in Table 2.

### 4 Results

#### 4.1 First-stage estimation results

Before 2SLS estimation, we first conduct a multicollinearity test and finalize the RHS variables to be included in the first- and second-stage models. We initially tested an extensive list of socioeconomic variables identified from the literature but dropped many of them considering their variance inflation factors (VIFs) and explanatory power. For example,
GDP per capita presents a very high VIF value due to its strong correlation with mean annual wage levels, and thus either variable has to be excluded to avoid a serious multicollinearity problem. In this case, we chose the latter, as it offers much stronger explanatory power. All RHS variables displayed in Table 3 are chosen through this process, and those used for our main model show VIF values ranging from 1.16 to 1.89. These values are substantially below the standard threshold of 5, and thus we safely conclude that our 2SLS hedonic regression is not subject to a serious multicollinearity problem (Kennedy, 2003).

The first-stage estimation results show that the proposed model behaves well in accordance with our hypotheses (Table 4). First, the three IVs overall show strong explanatory power for local PM levels with expected signs. TP is positively associated with $\text{PM}_{2.5}$ levels, and its coefficients are significant at the 1% level in both models. In other words, local PM levels of a given city tend to increase when the city is located in proximity to other cities with high PM levels. This result confirms that transboundary pollution significantly contributes to local air pollution in Chinese cities. In contrast to TP, PRE is negatively
associated with PM$_{2.5}$ levels, showing statistical significance at the 1% level in both models. As discussed earlier, this suggests wet scavenging effects on PM pollution removal.

In the case of TEMP, we test both linear and quadratic structures, given that energy demand is particularly high during hot and cold seasons (Deschênes & Greenstone, 2011). In Model 1 positing a linear pattern, the coefficient for TEMP is positive and significant at the 1% level. In Model 2 positing a nonlinear pattern, both TEMP and its quadratic term are significant at the 1% level and show opposite signs; the former has a positive sign while the latter has a negative sign. This suggests that the effects of TEMP on PM$_{2.5}$ levels take an inverted U-shape in China’s context. Of the two models tested, Model 2 is preferred as our main model, given its higher explanatory power measured in R square. This first-stage model is thus used for the follow-up second-stage estimation.

Among the covariates included in $Z_{i,t−1}$, only WAG shows statistical significance at the 5% level in both models. The positive coefficient for WAG is plain to understand, given that increased wage levels tend to drive up aggregate energy consumption—a main source of anthropogenic PM pollution.

### 4.2 Second-stage estimation results

The second-stage results demonstrate a significant pollution-imposed penalty on housing value (Table 5). Our central estimates shown in Model 1 suggest an elasticity of $-0.32$ in China’s context—a unit percentage increase in PM$_{2.5}$ levels tends to reduce housing prices by 0.32%. Alternatively, this result can be interpreted from a consumer’s perspective. That is, the elasticity of $-0.32$ means that Chinese citizens on average are willing to pay a housing premium of 0.32% in return for a unit percentage improvement in PM$_{2.5}$ levels. In our sample, this housing premium of 0.32% approximately translates into an MWTP.
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of RMB23/m² for a unit PM$_{2.5}$ concentrations reduction in µg/m$^3$ terms, during the period of 2005–2017. Conventional one-step fixed effects estimation, whose results are shown in Column [2] for comparison, also leads to a negative elasticity, significant at the 1% level. However, the elasticity of $-0.17$ in this case posits much weaker pollution-market feedback than our 2SLS-based estimate, due to failure to control for potential endogeneity. The socioeconomic controls included in $Z_{it-1}$ are all positively associated with housing prices, which coincides with our hypothesis, and are significant at the 5% or higher level.

A set of conventional specification tests supports the robustness of our 2SLS-based central estimates (Table 6). First, the Hausman test comparing our 2SLS model specification with a one-step fixed effects model rejects the null at the 1% level. This suggests that instruments to control for endogeneity are essential to ensure consistent estimation results. Second, an $F$-test imposing a restriction of $\pi_i = 0$ rejects the null at the 1% level. The $F$ statistic of 318 computed from the test is much larger than its conventional threshold of 10, so it can be concluded with confidence that our 2SLS model is not subject to a potential weak instrument problem. Finally, the Sargan test cannot reject the null of overidentification at the 5% level. The validity of the overidentification restriction suggests that the instrument exogeneity assumption—a key condition for consistent estimation results—holds.

Local housing market feedback on air quality tends to be more sensitive in larger cities (Table 7). Overall, inclusion of interaction terms still yields consistent macro results on the treatment, covariates, and IVs in terms of sign and significance, when compared with our central results displayed in Table 5. Both city-size interaction terms

**Table 5** Our second-stage estimation results in comparison with conventional one-step FE estimation results

|                      | LHS Variable: Housing Price (log) |
|----------------------|-----------------------------------|
|                      | [1]* 2SLS                          | [2] One-step FE                     |
| Treatment Variable   |                                   |
| PM$_{2.5}$ (log)     | $-3.17E-01$** (4.46E–02)          | $-1.70E-01$** (2.48E–02)           |
| Covariates with 1-year time lag ($Z_{it-1}$) |                  |
| Population (log)     | $3.58E-02$* (1.69E–02)            | $4.47E-02$** (1.68E–02)            |
| Wage (log)           | $1.29E-01$** (2.99E–02)           | $1.22E-01$** (2.99E–02)            |
| Manufacturing Share  | $1.32E-01$** (4.84E–02)           | $1.47E-01$** (4.83E–02)            |
| City Fixed Effects   | YES                               | YES                                |
| Year Fixed Effects   | YES                               | YES                                |
| Constant             | $7.08E+00$** (3.30E–01)           | $6.54E+00$** (3.01E–01)            |

*p < 0.05; **p < 0.01; standard errors are in parentheses
*a Main model for central results in this study

**Table 6** Model specification test results

|                    | Result                          |
|--------------------|--------------------------------|
| Hausman Test (H$_0$ : One-step fixed effects estimator is consistent.) | $p < 0.01$ |
| $F$-test on Weak Instruments (H$_0$ : Instruments are weak.) | $p < 0.01$ ($F = 317.86$) |
| Sargan Test (H$_0$ : Overidentification restrictions are valid.) | $p > 0.05$ ($J = 1.93$) |


are significant at the 5% or higher level and their coefficients present a negative sign. The negative coefficient for BIG1 (−0.026) augments the base elasticity by 8%, leading to an elasticity of −0.342 for those cities with an urban population of ≥5 million. Likewise, the negative coefficient of −0.008 for BIG2 intensifies the base elasticity by 2.5%, resulting in an elasticity of −0.324 for those cities with an urban population of 1 million to 5 million. This result suggests that residents in large Chinese cities are willing to pay an additional 3–8% housing premium for a unit % reduction in PM2.5 levels. Higher elasticity in large cities seems to reflect the fact that PM2.5 levels in China tend to be higher in larger cities and thus the marginal benefit associated with a unit % pollution reduction may be felt more by those who live in larger cities.

Another interesting result shown in the same table is a change in the elasticity across time periods. Both interaction terms including sub-period dummies are significant at the 1% level and show opposite signs. The base elasticity of −0.29 for earlier years increases in absolute value to −0.33 during the post-2008 period, but declines to −0.24 in the post-2014 period. On the one hand, increased housing market sensitivity to air quality in the post-2008 period seems to reflect growing public awareness of PM pollution and associated health risk after the Beijing Olympic Games (Kay et al., 2015). On the other hand, the decline in elasticity in the post-2014 period may be interpreted in connection with the increased stringency of anti-pollution regulations introduced in late 2013 and associated forward-looking market behavior. That is, implementation of strict air-quality control measures with ambitious pollution-abatement goals has clearly signaled in the market that substantial nationwide, urban air-quality improvement will follow in the near future. This positive prospect on air quality may then reduce the sensitivity of the market response to existing PM pollution (Freeman, 1979).

### Table 7

| Treatment Variable (x_it) | [1] 2SLS | [2] 2SLS |
|---------------------------|---------|---------|
| PM2.5 (log)               | −3.16E−01** (4.45E−02) | −2.89E−01** (4.52E−02) |
| Covariates with 1-year time lag (Z_{it−1}) |         |         |
| Population (log)          | 5.17E−02** (1.81E−02) | 3.50E−02* (1.69E−02) |
| Wage (log)                | 1.30E−01** (3.00E−02) | 1.36E−01** (2.99E−02) |
| Manufacturing Share       | 1.26E−01** (4.84E−02) | 1.35E−01** (4.85E−02) |
| Interaction Terms (T_{it})|         |         |
| BIG1*x_{it}               | −2.58E−02** (9.36E−03) |         |
| BIG2*x_{it}               | −7.87E−03* (3.60E−03) |         |
| T1*x_{it}                 | −3.92E−02** (1.46E−02) | 5.26E−02** (1.72E−02) |
| T2*x_{it}                 | 7.02E+00** (3.31E−01) | 6.92E+00** (3.33E−01) |

*p < 0.05; **p < 0.01; standard errors are in parentheses
4.3 Robustness and placebo tests

In this section, we discuss robustness and placebo test results. The robustness test is designed to see how sensitive our central results are with regard to $TP$, used as an instrument. As summarized in Table 8, we test seven alternative definitions in total by setting different $d_{ij}$ thresholds for sample truncation ([1a]–[1f]) and imposing first-order inverse distance weighting ([2]). Key findings of this study still hold, in that coefficients for $x$ (PM$_{2.5}$ elasticity of housing price) in all cases are significant at the 1% level, and exhibit only a marginal difference from our central estimate ([Ref]), ranging in $[-0.6%, 7.9%]$.

First, when those cities within a radius of 50 km and 100 km are excluded from the upwind area $(J)$ of city $i$ ([1a] and [1b]), estimated elasticities are $-0.315$ and $-0.292$, presenting a reduction of $0.6%$ and $7.9%$ from [Ref] (in absolute value), respectively. This difference of $\leq 7.9\%$ sets an upper limit for the potential influence of nearby cities within $\leq 100$ km on local housing markets of a given city. Second, our central results are also robust when upwind region $J$ is defined using different upper thresholds for $d_{ij}$. The lowest threshold value of 450 km ([1c]) leads to a marginal increase in elasticity by $\leq 0.6\%$ (in absolute value), while higher threshold values of 475 km, 525 km and 550 km ([1d], [1e] and [1f]) slightly reduce the elasticity by $\leq 1.3\%$ (in absolute value). Finally, first-order inverse distance weighting ([2]) also has marginal impacts on our central estimates based on second-order weighting. The estimated elasticity of $-0.316$ presents a $0.3\%$ increase in absolute value from [Ref].

In the meantime, our placebo test benchmarks a quasi-experiment, where the absence of placebo effects gives partial support to the validity of the causal mechanism specified in our 2SLS model. For testing purposes, we create a weak instrument ($TP_{W}$) by ignoring dominant wind directions and physical inter-city distance in computing $TP$, and estimate

| Table 8 Robustness test results |
|---------------------------------|
|                                | Coefficient for $x$ in 2nd Stage | % Change from [Ref] |
| [Ref] $TP_{it} = \sum_{j \in J} w_{ij} x_{jt}$ where $J = \{j \mid i \in I, d_{ij} \leq 500\}$ | $-3.17E-01** (4.46E-02)$ | $-$ |
| [1] $TP_{it} = \sum_{j \in J} w_{ij} x_{jt} \left(\max\left(d_{ij}/100,1\right)\right)^2$ where:
  | $[1a]$ $J = \{j \mid i \in I, 50 \leq d_{ij} \leq 500\}$ | $-3.15E-01** (4.48E-02)$ | $0.6\%$ |
  | $[1b]$ $J = \{j \mid i \in I, 100 \leq d_{ij} \leq 500\}$ | $-2.92E-01** (4.58E-02)$ | $7.9\%$ |
  | $[1c]$ $J = \{j \mid i \in I, d_{ij} \leq 450\}$ | $-3.19E-01** (4.47E-02)$ | $-0.6\%$ |
  | $[1d]$ $J = \{j \mid i \in I, d_{ij} \leq 475\}$ | $-3.16E-01** (4.48E-02)$ | $0.3\%$ |
  | $[1e]$ $J = \{j \mid i \in I, d_{ij} \leq 525\}$ | $-3.15E-01** (4.49E-02)$ | $0.6\%$ |
  | $[1f]$ $J = \{j \mid i \in I, d_{ij} \leq 550\}$ | $-3.13E-01** (4.49E-02)$ | $1.3\%$ |
| [2] $TP_{it} = \sum_{j \in J} w_{ij} x_{jt}$ where $J = \{j \mid i \in I, d_{ij} \leq 50\}$ | $-3.16E-01** (4.62E-02)$ | $0.3\%$ |

*p < 0.05; ** p < 0.01; standard errors are in parentheses

All models are estimated with a 2SLS specification given in Eqs. 1 and 3.
the 2SLS model using $TP_W$. Coinciding with our expectation, estimation results go against the placebo effect (Table 9). The first-stage results confirm that the proposed weak instrument is truly weak——$TP_W$ is not a significant regressor for $x$ at the 5% level. In this case, the second-stage results are also different from our central results—the effects of air pollution ($x$) on housing prices ($y$) are not significant at the 5% level. In sum, hypothesized treatment effects—pollution-imposed negative housing premium—disappear with a weak instrument, and this placebo-test result supports key findings from our original model specification.

5 Conclusions

In this study, we examine air-quality premiums capitalized into housing value, using an 13-year panel data for 237 prefecture-level Chinese cities. This study has two motivations. The first is to enrich the sparse hedonic literature on PM$_{2.5}$ in China’s context. We have so far found only two 2SLS-based panel studies, and thus the robustness of its results requires further empirical support. Our revealed preference approach can complement widely available stated preference WTP estimates, essential for further pollution impact studies but subject to large standard deviations. The other motivation is to test how air-quality premiums reflected in housing value may interact with local socioeconomic and policy environments. The existing Chinese hedonic literature focuses on the pre-implementation periods

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Table 9 Placebo test results

|                     | First Stage          | Second Stage          |
|---------------------|----------------------|-----------------------|
|                     | LHS Variable: PM$_{2.5}$ (log) | LHS Variable: Housing Price (log) |
| Treatment Variable ($x_i$) |                       |                       |
| PM$_{2.5}$ (log)    | −1.92E−01 (1.39E−01) |                       |
| Instrumental Variables ($D_{ij}$) |                       |                       |
| Transboundary Pollution ($TP_W$, log) | 1.31E−03 (1.96E−03) |                       |
| Precipitation (log) | −3.72E−02** (7.04E−03) |                       |
| Temperature (log)   | 1.08E+01** (1.52E+00) |                       |
| Temperature Squared (log) | −1.35E+00** (1.96E−01) |                       |
| Covariates with 1-year time lag ($Z_{i,t−1}$) |                       |                       |
| Population (log)    | −5.70E−02** (1.25E−02) | 4.33E−02* (1.88E−02) |
| Wage (log)          | 6.16E−02** (2.23E−02) | 1.23E−01** (3.10E−02) |
| Manufacturing Share | −1.01E−01** (3.60E−02) | 1.45E−01** (5.07E−02) |
| City Fixed Effects  | YES                  | YES                   |
| Year Fixed Effects  | YES                  | YES                   |
| Constant            | −1.80E+01** (2.95E+00) | 7.64E+00** (6.09E−01) |

*p < 0.05; **p < 0.01; standard errors are in parentheses

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1 In computing $TP_W$, weights for those cities located within the upwind area are set to be zero, while positive weights are given to cities located outside the dominant wind directions. Also, PM levels in remote cities located 100 km or farther outside a given city are treated with an equal weight, regardless of actual physical inter-city distance.
Impacts of air pollution on urban housing prices in China

Our results show a significant negative association between air pollution and housing prices in China’s context. During the period of 2005–2017, a unit percentage increase in PM$_{2.5}$ levels is associated with a 0.32% decline in housing value, presenting an elasticity of $-0.32$. This result is within the range of available elasticity estimates $[-0.43, -0.21]$. When compared with our central results, conventional one-step OLS regression leads to a much lower market premium on air quality (elasticity of $-0.17$), exhibiting a substantial downward bias as hinted at in the literature. Our central 2SLS-based estimate can alternatively translate into a MWTP (or housing premium) of RMB23/m$^2$ for a unit μg/m$^3$ reduction in PM$_{2.5}$ concentrations. However, it is a caveat that these estimates capture mean effects on an aggregate housing stock, and thus their interpretation in relation to a particular housing unit or type requires caution.

We find that the elasticity for PM$_{2.5}$ is subject to substantial variations by location and time. Urban housing markets in relatively large cities are found to be more sensitive to air quality (elasticity of $-0.342$ for those with an urban population of $\geq 5$ million; elasticity of $-0.324$ for those with an urban population of 1 million to 5 million) than those in smaller cities (elasticity of $-0.316$), presenting an additional housing premium of up to 8% for a unit percentage PM$_{2.5}$ concentration reduction. Greater housing premiums for clean air in larger cities may be justified given that marginal benefit from a unit percentage air-quality improvement can be greater in larger cities suffering more serious PM$_{2.5}$ pollution.

We also find a temporal variation in housing market response to air quality, where the elasticity of $-0.29$ for an initial period increases in absolute value to $-0.33$ in the post-2008 period and then falls to $-0.24$ in the post-2014 period. This trend seems to be associated with increased public awareness of PM-induced health risk after the 2008 Beijing Olympic Games and rational expectations arising from growing stringency of pollution regulations since the late FYP12 period.

Our study conveys a key policy implication: the market damage associated with PM pollution is substantial in China’s context, requiring consistent policy interventions for long-term pollution abatement. In 2017, for example, a 1 μg/m$^3$ increase in PM$_{2.5}$ concentrations is estimated to have caused a 0.5% loss in housing value in 237 prefecture-level cities. This suggests that around an 8% loss of the aggregate residential property value could have been avoided if those cities had met China’s class 2 national ambient air-quality standards (35 μg/m$^3$ in PM$_{2.5}$ levels). Our results also show that the elasticity in absolute value tends to decline with increased stringency of pollution control. This tendency posits an increasing convex damage function where the aggregate market damage associated with a unit percentage increase in PM levels grows much faster in higher pollution bands, and this nonlinear relationship adds another angle to the need for maintaining a reasonably low-pollution band. Given China’s current air quality, meeting a global alert level, such as the World Health Organization Air Quality Guideline level, can be attained only through consistent long-term efforts.

Appendix

See Table 10.
Table 10  List of cities included in sample

| Province   | Cities                                                                 |
|------------|------------------------------------------------------------------------|
| Beijing    | Tianjin, Shanghai, Chongqing                                          |
| Hebei (11) | Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingta, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui |
| Shanxi (11)| Taiyuan, Datong, Yangquan, Changzhi, Jincheng, Shuozhou, Jinzhong, Yuncheng, Xinzhou, Linfen, Luliang       |
| Inner Mongolia (8) | Hohhot, Baotou, Wuhan, Chifeng, Tongliao, Erdos, Hulunbeier, Wulanchabu |
| Liaoning (12)| Shenyang, Dalian, Anshan, Fushun, Benxi, Jinzhou, Fuxin, Liaoyang, Panjin, Tieling, Chaoyang, Huludao |
| Jinlin (8) | Changchun, Jilin, Siping, Liaojiu, Tonghua, Baishan, Songyuan, Baicheng |
| Heilongjiang (12)| Harbin, Qiqihar, Jixi, Hegang, Shuangyashan, Daqing, Yichun, Jiamusi, Qitaie, Mudanjiai, Heihe, Suihua |
| Jiangsu (4) | Xuzhou, Yancheng, Zhenjiang, Taizhou                                    |
| Zhejiang (10)| Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Qzhou, Zhoushan, Lushui |
| Anhui (15) | Hefei, Wuhu, Bengbu, Huainan, Maanshan, Huaibei, Tongling, Anqing, Huangshan, Chuzhou, Fuyang, Suzhou, Liuan, Chizhou, Xuncheng |
| Fujian (1) | Putian                                                                 |
| Jiangxi (10)| Nanchang, Jingdezhen, Pingxiang, Jiujian, Xinyu, Yingtan, Ganzhou, Jian, Fuzhou, Shangrao |
| Shandong (17)| Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Weifang, Jining, Taian, Weihai, Rizhao, Laiwu, Linyi, Dezhou, Liaoqing, Binzhou, Heze |
| Henan (17) | Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Anyang, Hebi, Xinxiang, Jiaozuo, Puyang, Xuchang, Luohu, Sanmenxi, Nanyang, Shangqiu, Xinyang, Zhoukou, Shandong |
| Hubei (2)  | Wuhan, Yichang                                                           |
| Hunan (13) | Changsha, Zhuzhou, Xiantan, Hengyang, Shaoyang, Yueyang, Changde, Zhangjiakou, Yiyang, Chenzhou, Yongzhou, Huaihua, Louden |
| Guangdong (21)| Guangzhou, Shaoquan, Shenzhen, Zuhai, Shantou, Foshan, Jiangmen, Zhanjiang, Maoming, Zhaoqing, Huizhou, Meizhou, Shanbei, Heyuan, Yangjiang, Qingyuan, Dongguan, Zhongshan, Chaozhou, Jieyang, Yunfu |
| Guangxi (14)| Nanning, Liuzhou, Guilin, Wuzhou, Beihai, Fangchenggou, Qinzhou, Guigang, Yulin, Baise, Hezhou, Hechi, Laibin, Chongzuo |
| Hainan (2) | Haikou, Sanya                                                            |
| Sichuan (17)| Chengdu, Zigong, Panzhihua, Luzhou, Deyang, Mianyang, Guangyuan, Suining, Neijiang, Leshan, Nanchong, Meishan, Yinan, Guangan, Dazhou, Bazhong, Ziyang |
| Guizhou (1) | Guiyang                                                                 |
| Shaanxi (9) | Xi’an, Tongchuan, Baoji, Xianyang, Weinan, Yanan, Hanzhong, Ankang, Shangluo |
| Gansu (12) | Lanzhou, Jiayuguan, Jinchang, Baiyin, Tianshui, Wuwei, Zhangye, Pingliang, Jiqun, Qingyang, Dingxi, Longnan |
| Qinghai (1) | Xining                                                                  |
| Ningxia (5) | Yinchuan, Shizuishan, Wuzhong, Guyuan, Zhongwei                           |
Funding  No funding was received for conducting this study.

Declarations

Conflict of interest  The authors have no relevant financial or non-financial interests to disclose.

Human and animal rights  This manuscript does not contain any studies involving human participants performed by any of the authors.

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