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Impacts of Air Pollution on Urban Housing Prices in China

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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

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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 and 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 and Friedrich 2005; Burnett et al. 2014; Matus *et al.* 2012; OECD 2016). Once inhaled, fine particulate matter—often measured as PM₁₀ (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% to 9.9% of China's historic gross domestic product (GDP) levels (Nam *et al.* 2019a; World Bank and 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 and 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 and 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 and 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 and Crocker 1971; Chay and 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 and 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 and 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 PM₁₀, 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 and Chen (2017) and Chen and Jin (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 valued? Air quality valuation is essential when policy makers conduct cost-benefit analysis in planning and evaluating pollution regulations (Mendelsohn and 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 and Mead 2004; Cohen *et al.* 2017; Matus *et al.* 2008; Nam *et al.* 2019a; Nielsen and 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 socioeconomic 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 and 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 and Crocker 1987; Brucato *et al.* 1990; Smith and Huang 1995). However, there are also studies that fail to find any significant correlations (e.g., Li and 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 and 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, 2SLS-based results tend to be consistent (e.g., Bayer *et al.* 2009; Chay and 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 PM₁₀ are cross-city analyses, and present an elasticity of -0.74 to -0.35. Among them, two 2SLS-based studies (Huang and 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 and Greenstone 2005). Two recent PM_{2.5}-focused panel studies (Chen and Chen 2017; Chen and 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 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 **Equation 1**, where x_{it} is PM_{2.5} levels in city i at time t ; $\mathbf{Z}_{i,t-1}$ and \mathbf{D}_{it} are matrices of city-level attributes and cross-boundary pollution controls, respectively; $\boldsymbol{\pi}_1$, and $\boldsymbol{\pi}_2$ are vectors of parameters to be estimated; α_i and η_t are city-fixed effects and year-fixed effects terms, respectively; C is a constant; and v_{it} is an error term.

$$x_{it} = \mathbf{Z}_{i,t-1}' \boldsymbol{\pi}_1 + \mathbf{D}_{it}' \boldsymbol{\pi}_2 + \alpha_i + \eta_t + C + v_{it} \quad (1)$$

Variables included in $\mathbf{Z}_{i,t-1}$ 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 \mathbf{Z} are also used as right-hand side (RHS) variables for second-stage regression. A one-year time lag is set between \mathbf{Z} and x to clarify the direction of causality and thus control for potential endogeneity.

In contrast, \mathbf{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 and 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 **Equation 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).

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

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 (**Figure 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.

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 **Equation 3**, where y_{it} is housing price in i at t ; β and γ are a parameter and vectors of parameters to be estimated, respectively; μ_i and λ_t are city-fixed effects and year-fixed effects terms, respectively; and ε_{it} is an error term. All other notations in the equation are identical to those in Equation 1.

$$y_{it} = \beta \hat{x}_{it} + \mathbf{Z}'_{i,t-1} \gamma + \mu_i + \lambda_t + C + \varepsilon_{it} \quad (3)$$

Control variables included in $\mathbf{Z}_{i,t-1}$ are as defined for Equation 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 \mathbf{Z} . This is to express y_{it} as a linear combination of controls (\mathbf{Z}) and instruments (\mathbf{D}). That is, plugging Equation 1 into Equation 3 transforms our original second-stage equation into **Equation 4**, where ϕ_1 , and ϕ_2 are column vectors of parameters.

$$y_{it} = \mathbf{Z}'_{i,t-1} \phi_1 + \mathbf{D}'_{i,t} \phi_2 + \mu_i + \lambda_t + C + \varepsilon_{it} \quad (4)$$

Then, an unbiased estimate for β can be obtained through $\boldsymbol{\varphi}_2 \oslash \boldsymbol{\pi}_2$ —a Hadamard division of the second-stage coefficient vector for \mathbf{D} by the corresponding first-stage coefficient vector.

In addition to our central estimates based on Equation 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 \mathbf{T}_{it} which contains the interaction terms between time period or city-size dummies and x (**Equation 5**).

$$y_{it} = \beta \hat{x}_{it} + \mathbf{Z}'_{i,t-1} \boldsymbol{\gamma}_1 + \mathbf{T}'_{it} \boldsymbol{\gamma}_2 + \mu_i + \lambda_t + C + \varepsilon_{it} \quad (5)$$

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 (T1) and post-2014 (T2)—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 and 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 (State Council 2013; Nam 2021). This action plan was announced in September 2013, and we set 2014 as the threshold for T2, 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 **Figure 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 $36'' \times 36''$ $PM_{2.5}$ concentration grids for China (V4.CH.02) developed by van Donkelaar *et al.* (2019) and the $60'' \times 60''$ 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 and Chen 2017; Chen and 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 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 and 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 $\mathbf{Z}_{i,t-1}$, 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 of RMB23/m² for a unit $PM_{2.5}$ concentrations reduction in $\mu\text{g}/\text{m}^3$ 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 $\mathbf{Z}_{i,t-1}$ 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 $\boldsymbol{\pi}_2 = \mathbf{0}$ 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 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% to 8% housing premium for a unit % reduction in PM_{2.5} levels. Higher elasticity in large cities seems to reflect the fact that PM_{2.5} 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 5% 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).

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 α (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 ≤ 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 the 2SLS model using TP_W .² 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 of the

² 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.

present strict pollution regulations introduced in late 2013, requiring an extension of the time horizon for analysis.

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 $\mu g/m^3$ 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 ≥ 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 $\mu\text{g}/\text{m}^3$ increase in $\text{PM}_{2.5}$ 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 $\mu\text{g}/\text{m}^3$ in $\text{PM}_{2.5}$ 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.

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Appendix: List of Cities Included in Sample

Province	Cities
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Province-level Municipalities (4)	Beijing, Tianjin, Shanghai, Chongqing
Hebei (11)	Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui
Shanxi (11)	Taiyuan, Datong, Yangquan, Changzhi, Jincheng, Shuozhou, Jinzhong, Yuncheng, Xinzhou, Linfen, Lvliang
Inner Mongolia (8)	Hohhot, Baotou, Wuhai, Chifeng, Tongliao, Erdos, Hulunbeier, Wulanchabu
Liaoning (12)	Shenyang, Dalian, Anshan, Fushun, Benxi, Jinzhou, Fuxin, Liaoyang, Panjin, Tieling, Chaoyang, Huludao
Jilin (8)	Changchun, Jilin, Siping, Liaoyuan, Tonghua, Baishan, Songyuan, Baicheng
Heilongjiang (12)	Harbin, Qiqihar, Jixi, Hegang, Shuangyashan, Daqing, Yichun, Jiamusi, Qitaihe, Mudanjiang, Heihe, Suihua
Jiangsu (4)	Xuzhou, Yancheng, Zhenjiang, Taizhou
Zhejiang (10)	Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Lishui
Anhui (15)	Hefei, Wuhu, Bengbu, Huainan, Maanshan, Huaibei, Tongling, Anqing, Huangshan, Chuzhou, Fuyang, Suzhou, Luan, Chizhou, Xuancheng
Fujian (1)	Putian
Jiangxi (10)	Nanchang, Jingdezhen, Pingxiang, Jiujiang, Xinyu, Yingtan, Ganzhou, Jian, Fuzhou, Shangrao
Shandong (17)	Jinan, Qingdao, Zibo, Zaozhuang, Dongying, Yantai, Weifang, Jining, Taian, Weihai, Rizhao, Laiwu, Linyi, Dezhou, Liaocheng, Binzhou, Heze
Henan (17)	Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Anyang, Hebi, Xinxiang, Jiaozuo, Puyang, Xuchang, Luohe, Sanmenxia, Nanyang, Shangqiu, Xinyang, Zhoukou, Zhumadian
Hubei (2)	Wuhan, Yichang
Hunan (13)	Changsha, Zhuzhou, Xiangtan, Hengyang, Shaoyang, Yueyang, Changde, Zhangjiajie, Yiyang, Chenzhou, Yongzhou, Huaihua, Loudi
Guangdong (21)	Guangzhou, Shaoguan, Shenzhen, Zhuhai, Shantou, Foshan, Jiangmen, Zhanjiang, Maoming, Zhaoqing, Huizhou, Meizhou, Shanwei, Heyuan, Yangjiang, Qingyuan, Dongguan, Zhongshan, Chaozhou, Jieyang, Yunfu
Guangxi (14)	Nanning, Liuzhou, Guilin, Wuzhou, Beihai, Fangchenggang, 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, Yibin, 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, Jiuquan, Qingyang, Dingxi, Longnan
Qinghai (1)	Xining
Ningxia (5)	Yinchuan, Shizuishan, Wuzhong, Guyuan, Zhongwei

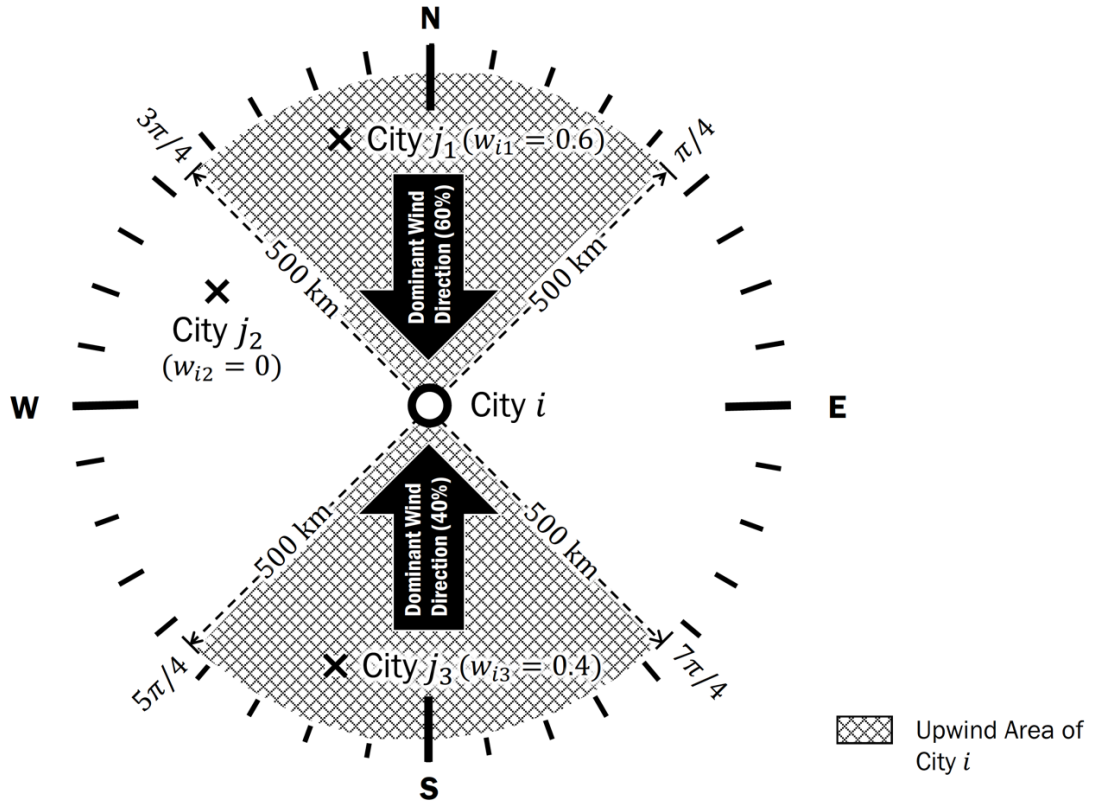


Figure 1. Illustrated Example of Weight (w_{ij}) Based on Dominant Wind Direction Shares.

Source: Created by the authors.

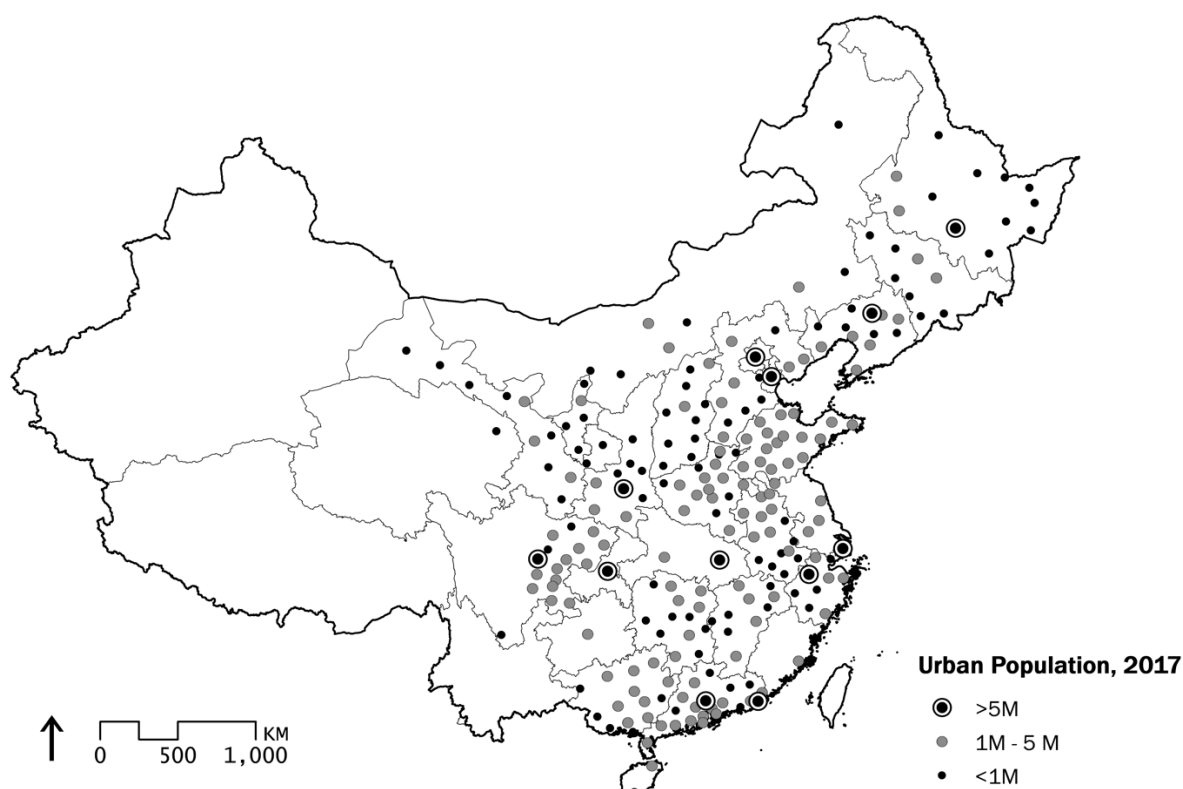


Figure 2. Spatial Distribution of 237 Prefecture-level Cities Included in Sample, with Their Population Size.

Source: Created by the authors from CEIC Data (2020).

Table 1. Application of Hedonic Regression in China's Context.

	<i>Sample</i>	<i>Method</i>	<i>Years Studied</i>	<i>Pollutant</i>	<i>Elasticity*</i>	<i>MWTP**</i> (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 (2015)	288 prefecture-level cities	2SLS	2011	PM ₁₀	-0.71	38
Zheng & Kahn (2007)	900 housing units in Beijing	OLS	2004-2005	PM ₁₀	-0.87	30
Zheng <i>et al.</i> (2010)	35 prefecture-level cities	OLS	1997-2006	PM ₁₀	-0.35	10
Zheng <i>et al.</i> (2014)	85 prefecture-level cities	2SLS	2006-2009	PM ₁₀	-0.74	28

Note: * 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 $\mu\text{g}/\text{m}^3$) increase in PM concentrations.

Table 2. Variable Definition and Summary Statistics.

<i>Variable</i>	<i>Definition</i>	<i>Obs.</i>	<i>Mean</i>	<i>Std. Dev.</i>
Variables of Interest				
Housing Price (<i>y</i>)	Annual mean sales price of newly-built commodity housing stock, in constant 2015 prices (RMB/m ²)	3,081	4.09E+03	2.98E+03
PM _{2.5} (<i>x</i>)	Annual mean PM _{2.5} levels (µg/m ³)	3,081	5.29E+01	18.3E+01
City Attribute Covariates (<i>Z</i>)				
Population (POP)	Hukou population within city proper (in 10 ⁴)	3,081	1.45E+02	1.92E+02
Wage (WAG)	Mean yearly wage, in constant 2015 prices (RMB)	3,081	3.86E+04	1.52E+04
Manufacturing Share (MFG)	Share of manufacturing employment	3,081	4.22E-01	1.42E-01
City and Time Dummies				
Large City 1 (BIG1)	1 if cities with population of ≥5 million; 0 otherwise.	3,081	4.35E-02	2.04E-01
Large City 2 (BIG2)	1 if cities with population between 1-5 million; 0 otherwise	3,081	4.25E-01	4.94E-01
Post-2008 (T1)	1 if 2009 or later, 0 otherwise	3,081	6.92E-01	4.62E-01
Post-2014 (T2)	1 if 2015 or later, 0 otherwise	3,081	2.31E-01	4.21E-01
Instrumental Variables (<i>D</i>)				
Transboundary Pollution (TP)	Inverse-distance-weighted PM _{2.5} levels in nearby upwind regions	3,081	2.13E+02	1.41E+02
Precipitation (PRE)	Annual mean precipitation (mm)	3,081	9.85E+02	5.88E+02
Temperature (TEMP)	Annual mean temperature (°F)	3,081	5.79E+01	1.02E+01

Table 3. Variance Inflation Factors.

	<i>VIF</i>
Transboundary Pollution (log)	1.51
Precipitation (log)	1.52
Temperature (log)	1.89
Population, with 1-year time lag (log)	1.17
Wage, with 1-year time lag (log)	1.17
Manufacturing Share, with 1-year time lag	1.16

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Table 4. First-stage Estimation Results.

	<i>LHS Variable: PM_{2.5} (log)</i>	
	[1]	[2] [†]
Instrumental Variables (\mathbf{D}_{it})		
Transboundary Pollution (log)	4.96E-01** (1.45E-02)	4.90E-01** (1.45E-02)
Precipitation (log)	-2.70E-02** (5.95E-03)	-2.89E-02** (5.94E-03)
Temperature (log)	4.17E-01** (9.68E-02)	6.69E+00** (1.29E+00)
Temperature Squared (log)		-8.14E-01** (1.67E-01)
Covariates with 1-year time lag ($\mathbf{Z}_{i,t-1}$)		
Population (log)	-2.03E-02 (1.07E-02)	-1.77E-02 (1.06E-02)
Wage (log)	3.79E-02* (1.90E-02)	4.07E-02* (1.88E-02)
Manufacturing Share	-4.88E-02 (3.07E-02)	-4.98E-02 (3.04E-02)
City Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Constant	-9.28E-03 (4.41E-01)	-1.20E+01** (2.50E+00)
R-square	0.47	0.48
Observations	3,081	3,081

Note: * $p < 0.05$; ** $p < 0.01$; standard errors are in parentheses.

[†] Main model for central results in this study.

Table 5. Our Second-stage Estimation Results in Comparison with Conventional One-step FE Estimation Results.

	<i>LHS Variable: Housing Price (log)</i>	
	[1] [†] 2SLS	[2] One-step FE
Treatment Variable (x_{it})		
PM _{2.5} (log)	-3.17E-01** (4.46E-02)	-1.70E-01** (2.48E-02)
Covariates with 1-year time lag ($\mathbf{Z}_{i,t-1}$)		
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)

Note: * $p < 0.05$; ** $p < 0.01$; standard errors are in parentheses.

[†] Main model for central results in this study.

Table 6. Model Specification Test Results.

<i>Test</i>	<i>Result</i>
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.)	$p > 0.05$ ($J = 1.93$)

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Table 7. Results of Second-stage Estimation with Interaction Terms.

	<i>LHS Variable: Housing Price (log)</i>	
	[1] 2SLS	[2] 2SLS
Treatment Variable (x_{it})		
PM _{2.5} (log)	-3.16E-01** (4.45E-02)	-2.89E-01** (4.52E-02)
Covariates with 1-year time lag ($Z_{i,t-1}$)		
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)
T2 * x_{it}		5.26E-02** (1.72E-02)
City Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Constant	7.02E+00** (3.31E-01)	6.92E+00** (3.33E-01)

Note: * $p < 0.05$; ** $p < 0.01$; standard errors are in parentheses.

Table 8. Robustness Test Results.

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

Note: * $p < 0.05$; ** $p < 0.01$; standard errors are in parentheses.

All models are estimated with a 2SLS specification given in Equations 1 and 3.

Table 9. Placebo Test Results.

	<i>First Stage</i>	<i>Second Stage</i>
	<i>LHS Variable: PM_{2.5} (log)</i>	<i>LHS Variable: Housing Price (log)</i>
Treatment Variable (x_{it})		
PM _{2.5} (log)		-1.92E-01 (1.39E-01)
Instrumental Variables (D_{it})		
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)

Note: * $p < 0.05$; ** $p < 0.01$; standard errors are in parentheses.

DECLARATIONS

Compliance with Ethical Standards

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