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Real Estate Valuation and Cross-Boundary Air Pollution Externalities: Evidence from Chinese Cities

Siqi Zheng · Jing Cao · Matthew E. Kahn · Cong Sun

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Abstract Within an open system of cities, compensating differentials theory predicts that local real estate prices will be higher in cities with higher quality non-market local public goods. In this case, more polluted cities will feature lower home prices. A city's air pollution levels depend on economic activity within the city and on cross-border pollution externalities. In this paper, we demonstrate that air pollution in Chinese cities is degraded by cross-boundary externalities. We use this exogenous source of variation in a city's air pollution to present new robust estimates of the real estate impact of local air pollution. We find that reductions in cross-boundary pollution flows have significant effects on local home prices. On average, a 10 % decrease in imported neighbor pollution is associated with a 0.76 % increase in local home prices. We also find that the marginal valuation of clean air is larger in richer Chinese cities, and *hukou* barrier of labor migration has been further phased out.

Keywords Air pollution · Cross-boundary externality · Hedonic · Chinese cities

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S. Zheng · C. Sun
Department of Construction Management and Hang Lung Center for Real Estate, Tsinghua University, Beijing, China

S. Zheng
e-mail: zhengsiqi@tsinghua.edu.cn

C. Sun
e-mail: suncong05@gmail.com

J. Cao (✉)
School of Economics and Management and CCWE, Tsinghua University, Beijing, China
e-mail: caojing@sem.tsinghua.edu.cn

M. E. Kahn
UCLA and NBER, Los Angeles, CA, USA
e-mail: mkahn@ioes.ucla.edu

Introduction

Many cities in China have extremely high air pollution levels. Based on ambient particulate concentration criteria of PM_{10}, twelve of the twenty most polluted cities in the world are located in China (World Bank 2007b).[1] In 2003, 53 % of the 341 monitored cities—accounting for 58 % of the country's urban population—reported annual average PM_{10} levels above 100 μg/m^3, and 21 % of cities reported PM_{10} levels above 150 μg/m^3. Only 1 % of China's urban population lives in cities that meet the European Union's air quality standard of 40 μg/m^3 (World Bank 2007a).

Urban air pollution in China is a function of economic activity within the city, due to local emissions from transportation, industrial production, and winter heating, and it is also a function of nearby pollution sources whose emissions are imported due to wind patterns. We refer to this second source of pollution as the cross-boundary externality.

In this paper we present new estimates of the real estate market consequences of such cross-boundary externalities. Depending on a city's geographical location, it will face different levels of "imported" dust and smoke emissions from neighbor cities' manufacturing production. A city's geography will also determine how much dust emissions it receives that is blown in from the sandstorm origin in Inner Mongolia.

These "imports" have major public health and quality of life consequences. In the past 30 years, Beijing suffered from an annual average of six sandstorms. In the severest sandstorm in 2006, 330 thousand tons of sand was blown into Beijing in 1 day.[2] Air pollution in Hong Kong represents another salient example.[3] While local diesel vehicles have contributed to local air pollution, the city's smog problem has been severely exacerbated from emissions imported from nearby Chinese manufacturing cities such as Zhaoqing, Qingyuan and Heyuan. Annual premature deaths attributed to the air pollution in 2008 are estimated to be 1,200 in Hong Kong (Edgilis 2009). As Chinese urbanites grow richer, the aggregate damage caused by such "pollution imports" grows.

Urban air pollution causes severe health problems and impedes day to day quality of life. The logic of compensating differentials predicts that real estate prices will be lower in polluted cities (Rosen 2002; Blomquist et al. 1988; Gyourko and Tracy 1991). This paper uses data from 85 Chinese cities to document that urban air pollution is an important disamenity in China. We present two different econometric approaches for estimating real estate hedonic regressions in order to quantify this effect. We also document heterogeneity in the degree of pollution capitalization into real estate prices as a function of city attributes.

This paper introduces several new ideas that were not explored in our earlier work that used OLS cross-city hedonic real estate methods to study the relationship between

[1] Particulate matter less than 10 μg in diameter, i.e. finer particles, are typically used in health damage assessments.

[2] See http://news.xinhuanet.com/politics/2006-04/19/content_4444861.htm.

[3] Some scholars have examined the relationship between the air quality and housing price in Hong Kong. For example, Chau et al. (2006) find air pollution has a significant negative impact on property prices, based on their semi-log regression, roughly an increase of 0.1 μg/m^3 in the air pollution level (suspended particulates) lowers property prices by 1.28 %. Edgilis (2009) conduct a conservative estimate in the west and central area of Hong Kong, and find that a 10 % drop in the level of SO_2 emissions can raise property value by 3.2–3.9 %, and a 20 % drop in SO_2 emission can raise housing price by 6.5–7.9 %.

air pollution and local real estate prices in China (Zheng et al. 2010). First, we document the importance of accounting for spatial externalities as a determinant of a city's air pollution. Second, we exploit the existence of cross-boundary spillovers as an instrumental variable in estimating cross-city hedonic real estate regressions. Such an instrumental variables strategy offers more credible estimates of the capitalization of air pollution than can be recovered using ordinary least squares. The overwhelming majority of cross-sectional hedonic real estate studies use OLS as the main estimation strategy. In this paper, we demonstrate that OLS estimates of real estate prices regressed on city attributes and local pollution levels underestimate the impact of pollution on local real estate prices. Below, we present a simple economic explanation for this statistical finding. We combine our results from estimating the role of cross-boundary pollution flows on local pollution levels and the hedonic relationship between local air pollution levels and local real estate prices and conclude that a 10 % decrease in imported neighbor pollution is associated with a 0.76 % increase in local home prices.

Third, we examine how the marginal urban residents' willingness-to-pay for clean air varies across Chinese cities as a function of a city's per-capita income and its migration *hukou* constraints. The hedonic pricing literature emphasizes that the pricing gradient reflects valuable information about the marginal consumer's preferences for local public goods (Rosen 2002). We document (all else equal) a larger pollution capitalization effect in richer and larger cities, while a smaller (though only marginally significant) capitalization effect in "*hukou* cities". Such "*hukou* cities" feature migration barriers to entry, thus it is not surprising that real estate prices are less responsive to local amenity levels.

Documenting the Cross-Boundary Air Pollution Externality

The first step in examining the real estate implications of cross-boundary air pollution is to document that there is a spatial externality. To demonstrate this, we estimate a city level air pollution production function as reported in Eq. (1):

$$\begin{aligned}\ln(PM_{it}) = a_0 + a_1 \cdot X_{it} + \alpha_2 \cdot \ln(NEIGHBOR_{it}) + \alpha_3 \cdot \ln(SANDSTORM_i) \\ + \alpha_4 \cdot NORTH_i + \alpha_5 \cdot NORTH\_BORDER_i + \alpha_6 \cdot SOUTH\_BORDER_t + \varepsilon_{it}\end{aligned} \tag{1}$$

Where PM_{it} is the PM_{10} concentration in city i in year t, X_{it} is a vector of city level attributes. PM_{10} emissions are mainly produced by the combustion of fossil fuels, industrial processing (i.e. cement processing) of urban manufacturing sectors and construction. Similar to the U.S literature on cross-city quality of life (Blomquist et al. 1988; Gyourko and Tracy 1991), our pollution measure is particulate matter. Up until the present, the only systematically available particulate matter measure across Chinese cities is PM_{10}.[4] Public health research has documented that particulate exposure raises mortality risk (Chay and Greenstone 2003).

[4] Total suspended particles (TSP) measures the mass concentration of particulate matter in the air. Within TSP, PM_{10} stands for particles with a diameter of 10 μm or less, and $PM_{2.5}$ stands for those with a diameter of 2.5 μm or less. Particulates that are 10 μm or greater are filtered and generally do not enter the lungs. Particulates smaller than 10 μm are likely to enter the lungs. Particulate matter that is smaller than 2.5 μm ($PM_{2.5}$) can enter into the Alveoli where gas exchange occurs. Throughout the world, ambient monitoring now focuses on PM_{10} and $PM_{2.5}$.

The PM_{10} concentration data are provided by the Data Center of PRC's Ministry of Environmental Protection (http://datacenter.mep.gov.cn/), which is estimated from the official Air Pollution Index (API) based on the MEP API calculation formula.[5] The PM_{10} data cover the years 2006 to 2009 for 85 cities, while the other variables from yearbooks cover the years 2005 to 2008 for 287 cities (as explained below). Merging these two data sets yields a sample including 85 cities for the 2006–2009 period. Variable definitions and summary statistics are listed in Table 1.

Equation (1) embodies standard measures of the scale of economic activity, climate conditions and industrial composition. In particular, the *X* vector includes such attributes as city population (*POP*), the employment share of manufacturing industry (*MANU*), rainfall (*RAIN*).[6] These city-level variables come from the China Statistic Yearbooks, China Urban Statistic Yearbooks and the China Regional Statistic Yearbooks. Due to data availability constraint, we are unable to include a direct measure of on-road vehicles. Vehicles emit $PM_{2.5}$ the most. Since we focus on PM_{10}, vehicle emission is less important than that from manufacturing activities. In U.S cities, population is extremely highly correlated with the city's vehicle count.

Controlling for these city-specific attributes, we are especially interested in empirical proxies for cross-boundary pollution externalities (*NEIGHBOR* and *SANDSTORM*), and exogenous geographic variables (*NORTH*, *NORTH_BORDER*, *SOUTH_BORDER*). As we will discuss below, this set of variables will play a key role as instrumental variables for the cross-city hedonic pricing models we will report.

We construct the *NEIGHBOR* variable to measure how city *i*'s PM_{10} at time *t* is affected by dust and smoke emissions from nearby cities' manufacturing firms (including coal-burning power plants).[7] Air pollutants are often carried by wind, so urban air quality is affected more by emissions from the cities located upstream of its

[5] The quality of China's API data has been debated . For instance, Wang et al. (2009) found his self-measured PM level in Beijing during Olympic period is correlated with official API, but 30 % higher. Andrews (2008) pointed out a likely systematic downward-bias around the "Blue Sky" standard (API less or equal to 100), and also highlighted a sampling downward bias for dropping monitoring stations in more pollution concentrated traffic areas in Beijing. These studies triggered some concerns on the measurement errors using Chinese official API data. Later studies suggest that Wang's measurement gap between the self-measured data and official API data is mainly due to sampling and methodological differences (Tang et al. 2009; Yao et al. 2009, Simonich 2009).A recent paper by Chen et al. (2011) use both API and AOD data to analyze the changes before and after Beijing Olympic. Their study suggests that the two different data sources provide similar results. In our study, we convert API index back to PM concentration data using the SEPA API formula. Andrews (2008) shows that this approach is reliable, especially when the main purpose is to study the cross-city variation for a large number of cities.

[6] Such reduced form estimates have been reported in U.S studies such as Kahn (1999).

[7] Recent atmospheric chemistry studies have documented the extent of cross-boundary pollution exports. Tong and Mauzerall (2008) highlight the importance of interstate emission transfer on local air quality, they use the CMAQ model simulate and construct a source-receptor matrix for all continental states of U.S. They found out over 80 % of the contiguous states, interstate transport of NOx emissions is more important than local emissions for summertime peak ozone concentrations. Liu et al. (2008) conduct a similar source-receptor matrix of sulfur emissions focusing on East Asian emissions on other continental regions, they find that present-day East Asian SO_2 emissions account for at least 20 % of total sulfate concentrations over the North Pacific at the surface, and East Asian SO_2 emissions account for approximately 30–50 % and 10–20 % of background sulfate at the surface over the Western and Eastern US. Saikawa et al. (2009) also apply MOZART-2 model, and find out China's aerosol emissions contribute significantly over neighboring regions by applying global models of chemical transport (MOZART-2) model. They estimate that, in the Korean peninsula and Japan, an annual average concentration of 1.4 $\mu g/m^3$ of $PM_{2.5}$ results from China's aerosol emissions.

Table 1 Variable definitions and summary statistics

Variable	Definition	Year	Obs.	Mean	Std. Dev.
*HP*1	Average sale price of newly-built homes (RMB/m^2)	2006~2009	340	3516.7	2311.5
*HP*2	Quality-controlled hedonic price of newly-built homes in 35 major cities(RMB/m^2)	2006~2009	140	5342.0	3037.0
PM	PM_{10} concentration in air (mg/m^3)	2006~2009	340	0.092	0.026
POP	Non-agricultural population size (million)	2006~2009	340	1.743	1.978
MANU	Share of manufacturing employment	2006~2009	340	0.261	0.128
EDU	Average year of schooling	2007	85	8.132	0.806
NEIGHBOR	Imported pollution from neighbor cities	2006~2009	340	1.562	0.684
WAGE	City mean annual wage per worker (10^4RMB)	2006~2009	340	2.814	0.785
POP1985	Historical non-agricultural population size (million) in 1985	1985	81	0.846	1.106
RAIN	Annual rain fall (mm)	2007	85	927.9	417.6
TEMP_INDEX	Temperature discomfort index	2007	85	18.1	5.55
SANDSTORM	The distance to the sandstorm origin (km)	—	85	1992.0	505.9
HUKOU	2=*hukou* accessibility is strictly constrained, 1=*hukou* accessibility is constrained to some extent; 0=*hukou* accessibility is not constrained	2007	85	0.071	0.258
HIGH_INC	Binary: 1=cities with income above the first tri-sectional quintile in the city income distribution, 0=otherwise	2007	85	0.330	0.473
MIDDLE_INC	Binary: 1=cities with income between the first and second tri-sectional quintile in the city income distribution, 0=otherwise	2007	85	0.330	0.473
LOW_INC	Binary: 1=cities with income below the second tri-sectional quintile in the city income distribution, 0=otherwise	2007	85	0.341	0.477
FIRST_TIER	Binary: 1=first-tier cities (Beijing, Shanghai, Shenzhen, Guangzhou), 0=otherwise	—	85	0.047	0.213
SECOND_TIER	Binary: 1=second-tier cities (provincial capital/ sub-provincial cities other than the four first-tier cities), 0=otherwise	—	85	0.365	0.484
THIRD_TIER	Binary: 1=third tier cities (cities other than the above two categories), 0=otherwise	—	85	0.588	0.495
SKILLCITY	Binary: 1=city's average years of schooling equals to or is above 9, 0=otherwise	2007	85	0.165	0.373
NORTH	Binary: 1=northern cities with winter heating (north of Huai River), 0=otherwise	—	85	0.353	0.481
NORTH_BORDER	Binary: 1=northern cities adjacent to Huai River, with its latitude below 35°· 0=otherwise	—	85	0.106	0.310
SOUTH_BORDER	Binary: 1=southern cities adjacent to Huai River, with its latitude above 30°· 0=otherwise	—	85	0.200	0.402

dominant wind direction. Based on our wind data, we assign different weights to cities in the dominant wind direction relative to cities in the non-dominant wind direction.[8] Specifically, *NEIGHBOR* is defined as:

$$NEIGHBOR_{it} = \sum_j w_{ij} \cdot smoke\ emission_{jt} \cdot e^{-d_{ij}}, \quad d_{ij} > 120km \tag{2}$$

(w_{ij}=1 indicates city *j* located in dominant wind direction of city *i*; w_{ij}=0 indicate otherwise.)

Where $smoke\ emission_{jt}$ is city *j*'s smoke emission in year*t* (measured in 10^6t),[9] d_{ij} is the distance between local city *i* and city *j* (in thousand kilometers) and $e^{-d_{ij}}$ is the value of a continuous and exponential decreasing function, so the weight declines as the distance between origin *j* and destination *i* increases. To minimize the likelihood that this variable is correlated with local city *i*'s economic activity, we exclude all the neighbor cities within 120 km from local city *i* in the above equation (i.e., d_{ij}>120 km). This variable's correlation with city *j*'s GDP per capita is extremely low (−0.04). The weight w_{ij} gives different weights for cities in the dominant wind direction and non-dominant directions. Figure 1 shows the spatial distribution of this *NEIGHBOR* variable. It highlights which cities are suffering the most from surrounding smoke emissions. The top five cities that suffer most from nearby cities' manufacturing emissions are Yantai, Weifang, Qinhuangdao, Kaifeng and Nantong.

"Sandstorm" represents a unique inter-regional long-distance transported pollutant. It is mainly composed of fine sediments originating in arid and semi-arid regions, and transported by strong winds to about 17 provinces in China. Similar impacts are also detected in Korea, Japan and even the west coast of the United States and the southern British Columbia, Canada (Chun 2000; McKendry et al. 2001). There have been growing concerns about the health damages caused by Asian sandstorms. Based on a case study in Beijing, Ai (2003) estimates the economic costs of sandstorm are greater than 2.9 % of Beijing's GDP in 2000. In our model, $SANDSTORM_i$ is city *i*'s distance to the sandstorm origin (Inner Mongolia). We use a logarithmic specification so the sandstorm's impact on a city's air quality also diminishes when the city is located further from the sandstorm's origin.[10]

The cities north of the Huai River and Qinling Mountains (it lies at roughly 33° latitude) receive subsidized heating in winter months, while the southern cities are not entitled to this centralized heating. This sector creates high emissions levels because heating's main energy source is coal (Almond et al. 2009).We include *NORTH,* which equals to one if the city is to the north of the heating line, in Eq. (1) to test for the role of winter heating on urban PM_{10} pollution. Almond et al. (2009) examine the discontinuity in air pollution above and below the Huai River due to this winter

[8] We collect monthly wind direction data of 287 prefecture-level cities (For the cities missing this data, we think the wind directions are almost the same as the nearby city/town) on China Meteorological Data Sharing Service System (http://cdc.cma.gov.cn/). After merging the wind directions (16 categories) into four common ones, we define dominant wind direction of a city in a standard year as monthly main wind direction(s) appear most in 12 months.

[9] To better measure the imported pollution from all neighbor cities, we use the smoke emission information of all 287 prefecture-level (or above) cities to construct this *NEIGHBOR* variable.

[10] Ideally we could also incorporate information on the direction and velocity of the sandstorm, which are different for different cities. Unfortunately we do not have access to accurate information. We test the robustness of our results by considering the relationship between the sandstorm's direction and the city's spring dominant wind direction (measured by the angle between these two. The main findings are robust to across to these changes (available upon request).

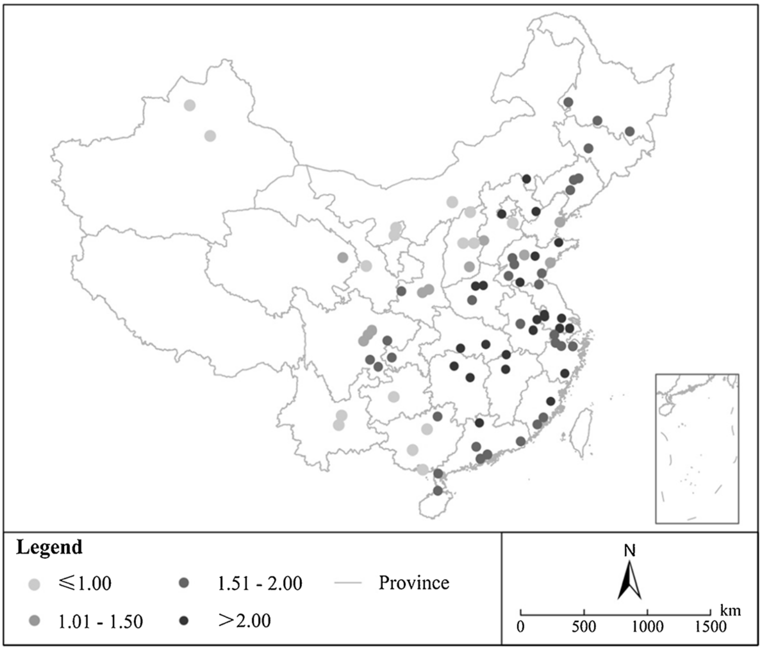

Fig. 1 Distribution of *NEIGHBOR* (Imported Emissions) in 2007 (wind-weighted)

heating effect. To see if their finding also holds in our sample, we include *NORTH_BORDER* (equals to one if the city locates above but very close to the heating line, with its latitude below 35° and above 33°) and *SOUTH_BORDER* (equals to one if the city locates below but very close to the heating line, with its latitude above 30° and below 33°), to compare if there is significant difference between the two coefficients. The cutoff numbers are borrowed from Almond et al. (2009).

Air quality in Chinese cities has been improving over time. The average PM_{10} concentration was 0.098, 0.092, 0.088 and 0.087 mg/m^3 for the years 2006, 2007, 2008 and 2009, respectively. Beijing experienced a great air quality improvement in the 3 years before the 2008 Olympic Game (0.162, 0.149, 0.124 mg/m^3 for 2006, 2007, 2008 respectively) due to factory shutdowns and short-term traffic control policies introduced. PM_{10} concentrations vary significantly across cities. In 2008, the dirtiest city (Lanzhou) had a PM_{10} concentration level (0.149 mg/m^3) four times higher than the cleanest city (Haikou, 0.038 mg/m^3).

Table 2 reports the air pollution production regressions. We estimate this regression using OLS. Column (1) excludes the cross-boundary externality variables and the three geographic variables. Several results emerge. First, the city size/ambient pollution elasticity equals roughly 0.11. Cities with larger manufacturing employment share have higher PM_{10} concentrations and this effect is statistically significant. Rainfall is good for mitigating air pollution. This equation can explain 30 % of the cross-city PM_{10} variation. In Column (2), our two cross-boundary pollution variables are included. They are jointly significant at 1 % level and improve the explanatory power (R^2) by 0.20. Imported pollution from neighbor cities' manufacturing activities has a very significant effect (at the 1 % level) on a local city's air pollution. A 10 %

Table 2 PM_{10} Production across 85 cities

Dependent variable	ln(*PM*)			
	(1)	(2)	(3)	(4)
ln(*POP*)	0.108*** (7.49)	0.0935*** (7.34)	0.0908*** (7.15)	
MANU	0.278* (1.71)	0.347*** (2.85)	0.307** (2.43)	
ln(*RAIN*)	−0.242*** (−6.51)	−0.157*** (−5.11)	−0.120*** (−2.68)	
ln(*SANDSTORM*)		−0.461*** (−10.01)	−0.418*** (−8.21)	−0.429*** (−7.90)
ln(*NEIGHBOR*)		0.165*** (8.93)	0.138*** (6.27)	0.130*** (7.04)
NORTH			0.0675 (1.49)	0.208*** (5.77)
NORTH_BORDER			0.154*** (3.13)	0.251*** (5.76)
SOUTH_BORDER			0.0886** (2.42)	0.144*** (3.88)
Constant	−0.843*** (−3.45)	1.972*** (6.34)	1.371*** (3.30)	0.684 (1.64)
*YEAR*2007	−0.0535 (−1.35)	−0.0269 (−0.81)	−0.0315 (−0.94)	−0.0334 (−0.91)
*YEAR*2008	−0.0904** (−2.26)	−0.0430 (−1.24)	−0.0511 (−1.47)	−0.0533 (−1.43)
*YEAR*2009	−0.0717 (−1.44)	0.00899 (0.22)	−0.00905 (−0.22)	−0.0577 (−1.58)
Joint F-test for IV variables		71.55*** (*SANDSTORM, NEIGHBOR*)	33.27*** (*SANDSTORM, NEIGHBOR, NORTH, NORTH_BORDER, SOUTH_BORDER*)	54.65*** (*SANDSTORM, NEIGHBOR, NORTH, NORTH_BORDER, SOUTH_BORDER*)
Observations	340	340	340	340
R^2	0.299	0.496	0.510	0.432

t statistics in parentheses

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

decrease of the *NEIGHBOR* variable reduces the PM_{10} concentration by 1.7 %. All else equal, a city's pollution level declines as its distance from the sandstorm origin in Inner Mongolian increases. In Column (3), we augment the pollution regression model to include *NORTH*, *NORTH_BORDER* and *SOUTH_BORDER*. Their coefficients are all positive (we acknowledge that *NORTH* may capture other attributes of northern cities). Northern cities adjacent to the heating line have higher PM_{10} concentration than southern cities adjacent to the line and this effect is marginally significant. This is consistent with Almond et al. (2009)'s finding of a pollution jump just north of the winter heating border. In Column (4) we only include the last five explanatory variables in the regression. This set of variables performs well in explaining the exogenous variation in a city's PM_{10} concentration. Below, we will use this set of variables as instrumental variables in estimating a hedonic real estate price regression.

New Estimates of the Cross-City Hedonic Home Price Hedonic Gradient

We estimate a series of pooled cross-sectional home price regressions. The equation is presented in Eq. (3).

$$\ln(HP_{it}) = \beta_0 + \beta_1 \cdot \ln(POP_{it}) + \beta_2 \cdot A_i + \beta_3 \cdot X_{it} + \beta_4 \cdot \log(PM_{it}) + \mu_{it} \qquad (3)$$

Where HP_{it} is home price in city i in year$t$. The "average home price" represents the average sales price of newly-built commodity housing units. Commodity housing sales account for the majority of the housing transactions (more than 70 %) in Chinese cities. There is no reliable price data for second-hand housing unit sales so we rely on this new housing price measure. The average annualized home price growth rate was 17 % for this time period. In 2009, the most expensive city is Shenzhen (14,389 RMB per square meter), and the cheapest city is Songyuan (1,156 RMB per square meter).[11] The large cross-city price variation is due to productivity and amenity differentials.

The "average home price" in the Yearbook is sometimes criticized for its inaccuracy in measuring price appreciation over time, due to poor quality controls. However, the reality is that there is no reliable quality-controlled home price index for such a large number of cities in China. Recognizing this issue, we also report results based on a subsample of 35 major cities, which is compiled by the Institute of Real Estate Studies at Tsinghua University (See Zheng et al. 2010 for details of the compiling methodology). We will use this hedonic price index as a robustness test.

In Eq. (3), A_i are a vector of natural amenities and human capital in city i. The key indicator for natural amenity we use here is the temperature discomfort index (*TEMP_INDEX*, see Zheng et al. (2010) for definition). We will also include the city's level of human capital (*EDU*, measured by average years of schooling). Rauch (1993) has demonstrated using U.S data that real estate prices are higher in more educated cities. In one specification we report below, we will also include the city's average wage. We include it in our specification to show that our major results are robust to its inclusion. In the X vector we include the city's manufacturing employment share which may affect labor demand and thus affect home price in a city.

[11] The exchange rate is roughly 7 RMB per U.S dollar.

Our Instrumental Variables Strategy

Past hedonic studies such as Gyourko and Tracy (1991) use ordinary least squares to estimate the hedonic real estate gradient reported in Eq. (3). Such an estimation strategy is based on the assumption that the hedonic price equation's error term is uncorrelated with the regression's explanatory variables. But, OLS estimates of Eq. (3) may yield inconsistent results of β_3 for at least two different reasons. First, air pollution is likely to be higher in those cities experiencing an economic boom (Zabel and Kiel 2000). Such booming cities will have more industrial activities taking place, and at the same time, households with greater incomes (due to the boom) will be more likely to own private vehicles. As a result of these facts, such booming cities will feature high home prices (because local labor demand is high) and high pollution levels. This will tend to bias the OLS estimates of PM_{10} towards zero.

The environmental regulation "J-curve" hypothesis offers a second explanation for why local air pollution could be correlated with unobserved determinants of local home prices. Selden and Song (1995) argue that richer nations are more likely to enact more stringent environmental regulation. If regulation is effective at lowering air pollution, then air pollution will be low in those areas that have effective, wealthy government. In this case, OLS estimates are likely to overstate the direct effect of PM_{10} because it proxies in part for good governance along a variety of dimensions (such as garbage pick-up and general "greenness").

Recent work in environmental economics based on U.S data offers a credible instrumental variables strategy. Bayer et al. (2009) instrument for a city's air pollution levels using nearby "origin" pollution that blows over to the "destination" city. Such emissions raise the destination's local ambient air pollution levels but are unlikely to be correlated with the hedonic pricing equation's error term. Other studies also find cross-border emission transport may contribute substantially to both source and downwind regions, therefore one city or region's air quality depends upon its own emissions and is affected by emissions from surrounding cities and regions (Tong and Mauzerall 2008; Liu et al. 2008).

We will follow this strategy to address the concern that PM_{10} is correlated with the error term in Eq. (3). In estimating Eq. (3), our *X* vector includes the city's population, manufacturing share, human capital level, and the temperature index. In estimating our first stage instrumental variables regression (see Eq. (1)), we include these *X* variables as explanatory variables. As in any instrumental variables regression, in addition to the *X* vector, the analyst must identify a set of variables that are correlated with the endogenous variable (*PM*) but should not directly appear in the outcome Eq. (3). We instrument for ln(*PM*) using the two cross-boundary externality variables (*NEIGHBOR*, *SANDSTORM*) and the three geographic variables (*NORTH, NORTH_BORDER*, *SOURTH_BORDER*).

We also address the concern about the potential endogeneity of city population size (*POP*). As documented in the U.S literature, the population is likely to migrate to those cities that are highly productive and that have high amenities. The error term in Eq. (3) will capture the unobserved location specific attributes and the urban population may be correlated with this. To address this concern, we use the city's population 20 years ago (year 1985) and the above exogenous variables to instrument for current city population. The year 1985 is the earliest year for which we have access to accurate city population statistics. In addition, the year 1985 was the very start of China's market economy, therefore there had been very little cross-city/rural-to-urban migration before that year.

Hedonic Real Estate Regression Results

Table 3 presents the hedonic real estate pricing regression results. In all of the regressions we cluster the standard errors by city. The first four columns are for the 85 city sample using the average home price (in logarithm) as the dependent variable. Column (1) reports OLS estimates. We find that bigger cities have higher home prices. The cross-sectional population elasticity is about 0.28. Manufacturing employment has a slightly positive effect on home price. We find a very significant capitalization effect of a city's climate comfortableness on home prices. As expected, home prices are significantly higher in the cities with higher human capital (measured in average years of schooling).[12] Holding these factors constant, we find the evidence that ambient particulate matter (*PM*) is negatively correlated with home prices, but the effect is not statistically significant.

As mentioned above, the OLS regressions may yield biased coefficient estimates of the *PM* effect due to possible endogeneity issues. To address this, we report IV estimates of Eq. (3) using the "externality" variables in Eq. (1) (Column (4) in Table 2) as our first stage to instruct *PM*, and using *POP*1985 to instruct *POP*.

In Table 3's Column (2), we first exclude the three geographic variables and only use the two cross-boundary variables to instrument for *PM*. The IV estimates yield more negative and significant *PM* elasticity than the OLS results.[13] Therefore the original OLS estimates are downward-biased to zero.[14] We estimate that a 10 % increase in a city's pollution is associated with a 7 % reduction in local real estate prices. By using *POP*1985 to instrument for a city's population *POP*, we can see that the coefficients of ln(*POP*) become smaller. In Column (3), we further include the three geographic variables when instrumenting for the local pollution level. The coefficient of ln(*PM*) becomes more negative. Combing with the first stage's regression (listed at the bottom of Table 3), it is shown that all else equal, a 10 % decrease of the imported pollution from neighbors (*NEIGHBOR*) is associated with a 0.76 % increase in home price.[15]

In Column (4), we include the city's wage as an extra explanatory variable. We find that prices are higher in cities that pay higher wages. As expected, due to potential multicollinearity between wage and other explanatory variables, we see most of the coefficients become smaller and less significant. The inclusion of this wage variable also shrinks the PM_{10} capitalization coefficient but it remains negative

[12] We acknowledge that we have a relatively "short" list of city attributes compared to the U.S quality of life literature due to data availability constraints. For example, we are unable to find city-level crime information.

[13] Our instrumental variables approach exploits exogenous variation in a city's PM_{10} level (due to imports of emissions). This approach addresses the concern that a city's pollution is caused by such local factors as booming industries and a rich populace that can afford to own and drive diesel vehicles. As we discussed above, such factors will bias the OLS estimate of PM's implicit price to zero.

[14] We find that the coefficient of *MANU* in the IV regressions is larger than that in OLS. This is consistent with the downward-biased *PM* coefficient in the OLS regression in which booming manufacturing activities increases both labor demand and local air pollution simultaneously.

[15] In the first stage, the coefficient of ln(*NEIBHOR*) is 0.103, so a 10 % decrease of *NEIGHBOR* will cause a 1.03 % decrease of ln(*PM*), and then 0.76 % decrease of home price (1.03 %×0.739=0.76 %).

Table 3 Cross-city hedonic home price regressions for 85 cities

Dependent variable	ln(*HP*1)				ln(*HP*1)		ln(*HP*2)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	IV	IV	OLS	IV	OLS	IV
ln(*POP*)	0.283^{***} (5.07)	0.238^{***} (3.45)	0.249^{***} (3.72)	0.138^{**} (2.41)	0.317^{***} (3.71)	0.159 (1.68)	0.337^{***} (3.68)	0.175^{*} (1.93)
MANU	0.0136 (0.04)	0.0764 (0.15)	0.100 (0.19)	0.150 (0.31)	0.762 (0.94)	0.844 (1.01)	0.619 (0.75)	0.687 (0.80)
TEMP_INDEX	-0.0244^{***} (−3.60)	-0.0234^{**} (−2.25)	-0.0222^{**} (−2.12)	-0.0173^{*} (−1.85)	−0.0112 (−1.02)	−0.0118 (−0.91)	-0.0209^{*} (−1.81)	−0.0224 (−1.67)
ln(*EDU*)	1.592^{**} (2.61)	1.841^{**} (2.34)	1.774^{**} (2.27)	0.883 (1.54)	1.664 (1.59)	2.104^{*} (1.81)	0.693 (0.63)	1.166 (0.97)
ln(*PM*)	−0.185 (−1.38)	-0.677^{**} (−2.24)	-0.739^{**} (−2.40)	-0.496^{**} (−2.10)	-0.548^{**} (−2.04)	-0.701^{*} (−1.87)	-0.516^{*} (−1.94)	-0.645^{*} (−1.76)
ln(*WAGE*)				0.408^{***} (5.46)				
Constant	4.438^{***} (3.50)	2.932 (1.62)	2.905 (1.59)	4.240^{***} (3.00)	3.037 (1.28)	1.987 (0.78)	5.509^{**} (2.35)	4.476^{*} (1.77)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	340	324	324	324	140	140	140	140
R^2	0.563	0.401	0.384	0.616	0.500	0.360	0.482	0.346

First-stage regression underlying Column (3):

$$\ln(PM) = 2.439 + 0.141 \times \ln(POP85) + 0.337 \times MANU + 0.006 \times TEMP\_INDEX - 0.769 \times \ln(\mathrm{EDU}) - 0.452 \times \ln(\mathrm{SANDSTORM}) + 0.103 \times \ln(NEIGHBOR) + 0.094 \times NORTH + 0.190 \times NORTH\_BORDER + 0.080 \times SOUTH\_BORDER + \text{Year dummies}$$

Joint F test for ln(*SANDSTORM*), ln(*NEIGHBOR*), *NORTH*, *NORTH_BORDER*, *SOUTH_BORDER*: $F=33.93^{***}$

t statistics in parentheses; standard errors clustered by city

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

and statistically significant. We view this regression to be a robustness test. The typical U.S hedonic real estate regression is viewed as a reduced form regression and the explanatory variables are quantities of location specific attributes rather than prices such as the price of labor (see Blomquist et al. 1988; Gyourko and Tracy 1991). Such studies use high quality U.S micro data to estimate separate hedonic wage regressions to measure how non-market local public goods are capitalized into both real estate prices and wages. In this paper, our focus is solely on the determinants of local real estate prices.[16]

To test the robustness of our results to different home price measures as well as to compare our findings with those in Zheng et al. (2010), we estimate both OLS and IV regressions using the hedonic quality-controlled home price index (*HP*2) and average home price (*HP*1) for the subsample of 35 cities (Column (5) to (8)). The signs of the amenity variable coefficients are quite consistent with those estimates using the average home price measure. ln(*PM*) holds a significantly negative sign in both OLS and IV regressions, and in both cases OLS estimates are downward biased, consistent with what we find for the whole sample. The sizes of PM_{10} capitalization effects are quite similar for both price measures, with that for average sale price a little bit higher than that for hedonic price index.[17] The comparability of our results across these two different data sources raises our confidence in the 85 city sample. For the sake of keeping a large number of cities in our sample, we will report our results based on this average price measure thereafter.

Evidence on the Rising Demand for Clean Air

The Chinese urban population is enjoying increased income and the average urbanite is increasingly well educated. Such households are likely to be increasingly willing to pay more to protect their health and thus willing to pay more to avoid urban air pollution. Another trend is that the *hukou* constraint on labor mobility is likely to be further phased out in the near future.[18] With a higher degree of free mobility, people

[16] It is important to note that we include a city's population in each of our hedonic price regressions. This population variable is likely to proxy for local productivity effects as the population will move to those areas that are more productive.

[17] In our 2010 RSUE paper (Zheng et al. 2010), we included the *PM* measure in levels in our home price hedonic regressions. Here we include the *PM* measure in logarithm. It is still significant but the *t*-statistic is smaller. To further verify the consistence between the two estimate versions, we estimate the regression in Column (7) with *PM* measure in levels. Its coefficient is statistically significant at 5 % level (t=2.15). In this paper we keep *PM* in logarithm for the sake of easily calculating elasticities.

[18] The *hukou* system, put in place in the 1950s, was to register people by their hometown origin and by urban versus rural status for the purpose of regulating migration. In the wake of transition to a market economy, the *hukou*'s regulation on population mobility was relaxed. Population mobility, especially rural to urban migration, was substantially elevated in the 1990s when urban housing market and labor market were liberalized and private sector employment grew rapidly with the inflow of foreign direct investment (FDI) to Chinese cities. Nevertheless, hukou remains important for rationing access to local public services and social security benefits; residents without local urban *hukou* can be denied access to public schools, public health care, public pensions and unemployment benefits in the city. *hukou* regulations are being eased in many Chinese cities, but the hurdles for getting *hukou* in major cities remain high and few rural migrant workers could expect to overcome them. A recent study at the Beijing Institute of Technology estimates that, tens of millions of people living in cities without urban *hukou* are denied access to these public services. ("Mismanaging China's rural exodus." Financial Times, 2010-03-12, http://www.ftchinese.com/story/001031699.)

can migrate to cities with higher wage and better quality of life. This arbitrage process will mean that local public amenities will have higher capitalized prices.

In Table 4, we test these hypotheses based on our instrumental variable estimation strategy. The first two columns report the time trend of the clean air premium. Since our time period is relatively short (4 years), we split it into two sub-periods: 2006 to 2007 and 2008 to 2009. We can see that the absolute value of this premium rose slightly from 0.72 to 0.75. This trend is quite similar to the results reported in Zheng et al. (2010) using data from 35 major Chinese cities during 2003 to 2006. After we include city wage as an additional explanatory variable, this trend still persists. The coefficient of ln(*PM*) is significant and its absolute value is rising over time (these results are available on request).

We construct a *HUKOU* variable to measure how restrictive the *hukou* constraint in a city is (see Table 1 for definition). The direct *hukou* restriction on labor mobility was phased out in the wake of transition to a market economy. A worker can work in a city without urban local *hukou*. As a result, population mobility, especially rural to urban migration, increased sharply in the 1990s. Therefore, urbanites in China are able to migrate to areas that offer higher wage and better quality of life (Zheng et al. 2009). Nevertheless, the *hukou* remains important for rationing access to local public services and social security benefits. Residents without local urban *hukou* can be denied access to public schools, public health care, public pensions and unemployment benefits. In our econometric specifications, a larger value of *HUKOU* means a stricter entrance restriction.

In Table 4's Column (3) we see that those cities with higher entrance barrier typically have higher home prices, but the price premium for clean air is smaller (marginally significant), which is consistent with the incidence theory that in those cities with barriers to entry it can be the case that a city can have high amenities but relatively low real estate prices. In Column (4) and (5) we interact ln(*PM*) with *HIGH_INC and MID_INC* (high-income cities and middle-income cities, with low-income cities as the default category, see Table 1 for definition) as well as *SKILLCITY* (cities with higher average years of schooling) dummies, respectively. We find that as the average resident in a city becomes richer and more educated, his willingness-to-pay for clean air does rise. Though we only find a slightly negative interaction term in Column (5) (perhaps due to the inaccurate city-level measure of average years to schooling), this rising capitalization trend is quite significant in Column (4). We also interact first-tier and second-tier city dummies (*FIRST_TIER*, *SECOND_TIER*, with third-tier cities as the default, see Table One for definition) with ln(*PM*), to find that urban households in larger cities have higher willingness to pay for clean air.

Conclusion

Air pollution has caused severe health damage in China (Wang and Mauzerall 2006; Ho and Nielsen 2007). The World Bank (2007a, 2009) estimates that 13 % of all urban premature deaths may be due to ambient air pollution. The overall health damage due to air pollution is roughly 3.8 % of GDP in China (World Bank 2007a, 2009). Exposure to outdoor air pollutants increases the incidence of lung cancer, cardio respiratory diseases and possibly low birth weight (Pope et al. 2002; Dockery et al. 1993; Almond et al. 2009).

Table 4 Cross-city hedonic home price regressions allowing for differential city effects

Dependent variable	ln(*HP*1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Year	2006~2007	2008~2009	2006~2009	2006~2009	2006~2009	2006~2009
ln(*POP*)	0.263^{***} (3.93)	0.230^{***} (3.30)	0.229^{***} (4.00)	0.197^{***} (3.28)	0.255^{***} (4.11)	0.144^{**} (2.25)
MANU	0.418 (0.84)	−0.351 (−0.57)	0.205 (0.42)	0.142 (0.27)	0.103 (0.19)	0.503 (1.03)
TEMP_INDEX	-0.0225^{**} (−2.10)	-0.0218^{**} (−2.09)	-0.0175^{*} (−1.70)	-0.0206^{**} (−2.05)	-0.0208^{*} (−1.82)	-0.0158^{*} (−1.86)
ln(*EDU*)	1.937^{**} (2.40)	1.588^{**} (2.06)	1.088 (1.54)	1.150^{*} (1.74)	1.291 (1.55)	0.631 (0.85)
HUKOU			2.107^{**} (2.11)			
HUKOU × ln(*PM*)			0.595 (1.42)			
HIGH_INC × ln(*PM*)				-0.200^{***} (−4.08)		
MID_INC × ln(*PM*)				-0.0712^{**} (−2.30)		
SKILLCITY × ln(*PM*)					−0.0622 (−0.86)	
FIRST_TIER × ln(*PM*)						-0.428^{***} (−4.17)
SECOND_TIER × ln(*PM*)						-0.137^{**} (−2.41)
ln(*PM*)	-0.721^{**} (−2.55)	-0.749^{**} (−2.17)	-0.659^{**} (−2.23)	-0.480^{*} (−1.74)	-0.725^{**} (−2.38)	-0.547^{**} (−2.28)
Constant	2.520 (1.35)	3.582^{*} (1.98)	4.359^{**} (2.45)	4.525^{***} (2.75)	3.902^{**} (2.11)	5.268^{***} (3.63)
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162	162	324	324	324	324
R^2	0.387	0.313	0.465	0.566	0.394	0.540

t statistics in parentheses; standard errors clustered by city

$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Based on a sample of 85 Chinese cities, we have presented new evidence concerning how real estate prices are affected by local pollution. We find that real estate prices are lower in high polluted cities and this discount is likely to grow over time when the average resident in a city becomes richer and more-educated. The further relaxation of the residential mobility constraint (*hukou*) will also push this capitalization growth. Given that ambient air quality has recently improved in several of China's cities, this rising capitalization evidence suggests that demand for clean air is rising in China.

We have generated these facts using an instrumental variables approach where we have exploited an important, plausibly exogenous source of variation in local air pollution. By collecting spatial data on the cross-boundary flows in pollution from origin to destination, we have generated more robust hedonic estimates of the value of avoiding air pollution. Our calculations show that on average, a 10 % decrease of the imported pollution from neighbors is associated with a 0.76 % increase in home prices. Such capitalization effects through real estate prices are sometimes ignored in policy incidence studies when conducting cost-benefit analysis of environmental policy analysis, however they may dominate other household welfare changes. Our paper provides a reliable hedonic gradient estimate for estimating the social benefits associated with public policies intended to mitigate the challenge.

As China's urbanites grow richer over time, their desire for living in clean, low risk cities will rise. Costa and Kahn (2004) argue based on U.S evidence that the statistical value of life rises faster than per-capita income growth. If this result extends to the case of China, then this means that public policies that help to mitigate the cross-boundary pollution problem will have increasing value to Chinese urbanites over time. Given that air pollution is a local public bad, such air pollution reductions will be especially valuable in heavily populated downwind areas. We recognize that the costs of reducing the origin pollution will be an important factor in determining optimal policy, so air pollution control efforts should not be constrained within a city itself but need to be coordinated in a larger region.

Our results imply that public policies that reduce cross-boundary pollution flows will simultaneously improve public health in the destination cities and lead to higher real estate prices. Whether real estate prices rise quickly in such improving areas hinges on the city's *hukou* system, and whether potential migrants to the city are aware of the amenity improvements.

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