Negotiating Housing Deal on a Polluted Day: Consequences and Possible Explanations

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Abstract

The topic of air pollution has drawn considerable attention globally. In this paper, we examine the *immediate* effect of air pollution on a substantial decision, that is, a housing purchase. By linking housing purchasing behavior with the air quality in Beijing, we document market participants' behaviors unexplained by rational economic theories. Our main result suggests that an increase of the $PM_{2.5}$ by 100 on the day of the negotiation leads to an approximately 0.19% increase in the per square meter transaction price. This translates into a total of 1.17 million *yuan* increase on a typical day. Using heterogeneous analyses, we rule out rational explanations and demonstrate that our empirical results are consistent with behavioral theories under weak assumptions.

Keywords: Air Pollution; Housing Market; Salience; Projection Bias

JEL Codes: D91; R31; L85; Q51

1 Introduction

The air pollution problems in developing countries have drawn considerable public attention from policy makers and researchers. A growing strand of literature tries to understand how air pollution affects individual behaviors. For instance, people may purchase masks and air purifiers to protect themselves from polluted air. Alternatively, they may be more willing to migrate to cleaner cities or countries as a more expensive protective measure. In addition to protective behaviors, air pollution may induce other behavioral changes in the context of insurance purchases (Chang et al.), stock investments(Li et al., 2017), and decision-making in the lab(Chew et al., 2017).[1]

In this paper, we examine the impact of air pollution on the real estate market in Beijing. In particular, we examine the *immediate* effects of severe air pollution on housing purchases. Housing transactions are a substantial outcome because the monetary amount associated with each transaction is large relative to households' income, and the consequences of housing purchases can endure for a long period or even one's entire life. We believe that this particular setting is suitable to test for immediate behavioral responses or behavioral biases for two reasons. First, given the extraordinarily high housing prices in Beijing, purchasing a house is a monumental decision in one's life; thus, it would be difficult to imagine that a buyer deliberately changes their mind just because of the air pollution on the contracting date. Second, as shown in Figure 1, air pollution is a relatively common phenomenon in Beijing, and people usually are not surprised by a severely polluted day.[2] Therefore, observing a single polluted day should not change their belief over

[1] Chang et al. find that people are more likely to purchase health insurance through a call center on polluted days and more likely to cancel these subscriptions afterwards. They argue that this type of behavior is consistent with projection bias, that is, the type of behavioral bias which refers to the tendency of over-predicting the degree to which one's future tastes will resemble one's current tastes. Using stock trading data, Li et al. (2017) find that air pollution on the trading day intensifies the disposition effect of stock traders. Chew et al. (2017) conduct decision-making experiments in the laboratory on days with various pollution levels and observe that individuals exhibit a higher level of risk aversion and impatience on polluted days.

[2] For example, see the topic about air pollution in Beijing by the South China Morning Post: http://www.scmp.com/topics/beijing-air-pollution. In addition, Chang et al. conduct a survey in Bei-

the long term about the local air pollution level; thus, this phenomenon should not change their mind about how much to spend on a house.

A barrier to studying the impacts of air pollution on housing deal negotiations is that the types of data available to the researchers do not have information on the specific date that the buyer and seller negotiate the price, which is the most relevant occasion to examine the immediate behavioral response to air pollution. In this study, we have access to a major housing brokerage firm's transaction data in Beijing with more than 120,000 transactions of second-hand houses. There are three unique features of the data for research purposes. Firstly, the data record the exact date when the buyer and seller negotiated the price and signed the contract immediately after, allowing us to match the air pollution level of the negotiation day to the housing transactions. Secondly, unlike most studies that examine purchasing behavior in a posted offer market, we observe the deal price of each transaction. This helps us rule out some rational explanations for the empirical results. Lastly, the data provide basic demographics of the buyers, including their birth place, age, and gender, as well as characteristics of the houses. This feature allows us to further test possible mechanisms with heterogeneous analyses.

In addition to the unique features of the dataset, the context of housing market and air pollution is different from other commodity markets in the literature, that is, the immediate or contemporaneous effects of heavy air pollution on housing values may be different from its long-run effects. Matching the air pollution level for the date that the buyers and sellers negotiate the price and sign the contract with the actual transaction price, we find that for every 100 increments in $PM_{2.5}$, the housing transaction price is actually 0.19% higher, after controlling for housing characteristics, community fixed effect, year-by-month fixed effect, day-of-the-week fixed effect, weather, and a dummy variable for holidays. Using the average transaction price and volume on a typical day, the calculated total increase, due to a 100 increase in $PM_{2.5}$, is about 1.7 million *yuan*. Given that

jing and the results show that people do not update their belief about local pollution levels based on a single-day observation.

the days with moderate pollution in Beijing are common, this is a economically significant amount. In addition to the effect on transaction price, we find that the transaction volumes are not declining and might be higher on severely polluted days. We rule out the possibility that the results are due to pollution's effect on the cognitive ability of home buyers, which may affect the bargaining outcomes.

Our evidence suggests that the positive association between air pollution and housing transaction prices is likely due to the salience thinking of home buyers (Bordalo et al., 2012, 2013a,b) under fairly weak assumptions. [3] Specifically, the buyer's attention is drawn to the living quality by the heavy pollution; thus, price becomes less salient. Consequently, on a polluted day, buyers who do not currently own a house would accept a higher price in the price negotiation, which then leads to a higher probability of a deal if the sellers do not change their behavior according to air pollution levels. We find that the behavioral response likely pertains to first-time home buyers in Beijing (non-local buyers who are young and buying smaller-sized residences) who had no experience owning a house. Consistently, we find no effect of air pollution on transaction prices of experienced buyers who already owned a house in Beijing prior to the transaction. As an supplementary evidence, we find that Baidu's (a search engine in China similar to Google) searches for home-purchase related key words significantly increases on polluted days. In addition, the number of website visits to Soufun, a national housing brokerage firm in China, increases on polluted days as well. All these evidence collected from different sources indicates that people tend to value housing more on polluted days due to the salience of living quality.

Our paper makes two major contributions. First, we contribute to the rich literature on the consequences of air pollution by studying its contemporaneous effect on housing transactions. In particular, our research is most relevant to the papers studying the impact of air pollution in the housing market and financial market. Chay and Greenstone (2005)

[3] The empirical evidence is also consistent with projection bias (Loewenstein, 2004; Loewenstein et al., 2003) though under stronger assumptions. We discuss this in section 7.2 in the paper.

find that a lower level of air pollution induced by the Clean Air Act in the mid-1970s is associated with higher housing prices at that time. Instead of examining the relatively long-run effect of air pollution on housing prices, the current study focuses on the contemporaneous effect of air pollution on housing prices due to individual irrationality, which has never been documented in the air pollution literature. Such behavioral distortion has important welfare implications because the monetary loss associated with such an effect is non-negligible. In the stock market, a paper by Heyes et al. suggests that a higher level of $PM_{2.5}$ in Manhattan is associated with significantly lower same-day stock returns, which is likely driven by pollution-induced changes in mood or cognitive function. Our research is also closely related to a growing body of literature studying the consequences of air pollution in China, which is one of the most pressing social problems in this country (Chen et al., 2016, 2013a,b; He et al., 2016; Ito and Zhang, 2016; Liu and Salvo, 2018; Mu and Zhang, 2014; Qin and Zhu, 2018; Sun et al., 2017; Viard and Fu, 2015; Zhang et al.).

Second, we provide the first evidence consistent with salience theory (and possibly projection bias) in the housing market. Decisions made by housing market participants are substantial for their lifetime well-being. Thus, salience thinking or projection bias is likely to lead to unfavorable outcomes. Busse et al. (2015); Conlin et al. (2007), among others, assert the importance of testing for projection bias in the housing market in their studies on projection bias. Unlike purchasing winter clothes or a car, mistakes in the housing market endure for a much longer time and are much more costly to correct. According to our review of the literature, we are also the first to test salience and projection biases in a bilateral negotiation setting. All empirical studies have relied on the volume of transactions or propensity of purchasing to demonstrate projection bias. We differentiate ourselves by examining both transaction price (thus inferring willingness to pay) and volumes in our empirical analysis.

The remainder of the paper is as follows. Section 2 introduces the background infor-

mation on the housing market in Beijing; Section 3 presents the air pollution data and housing transaction data; Section 4 discusses the hypotheses and identification strategy including instrumental variable estimates; Section 5 presents the main results; Section 6 discusses possible rational explanations for these results; Section 7 proposes behavioral explanations; and Section 8 concludes.

2 Housing Market in Beijing

According to the 2010 population census, approximately 60% of the households in Beijing live in self-owned houses, and the rest of the households live in rented housing units.[4] Most of the renters are non-local residents not born in Beijing, and their living conditions are generally worse than homeowners', which is typical in first tier cities in China.[5] For example, in Beijing, the average occupied space *per person* is 18.43 square meters for renters; this number more than doubles (38.15 square meters) for home owners of second-hand houses.[6] Even worse, more than 75% of the households living in rented units in Beijing must share either kitchen or bathroom with other tenants, whereas less than 3% of homeowners must do so (Zhen and Lv, 2011). In addition, the regulatory system is pro-landlord in the rental market in China and lacks the protection of tenants' rights.[7] A survey conducted in Beijing shows that 77.4% of the renters worried about the violation of rental contracts by the landlord, such as rent increases and early termination of contracts (Zhen and Lv, 2011). Living in rented houses is perceived as a temporary living arrangement while renters save for their down payment.

The housing market in Beijing has been booming in the past decade. As suggested by Fang et al. (2015), the housing price in Beijing increases much faster than the disposable

[4]Authors' calculations from the 2010 population census of Beijing.

[5]First tier cities in China refer to the four largest metropolitan areas, i.e., Beijing, Shanghai, Guangzhou, and Shenzhen.

[6]Authors' calculations from the 2010 population census of Beijing.

[7]Please refer to the following link for cross-country comparisons of tenants' law: http://www.globalpropertyguide.com/Asia/china/landlord-tenant-law.

incomes of its residents. The average housing price in Beijing in December 2015 was approximately 39,000 *yuan* (approximately USD 5,700) per square meter (Figure 2). To curb speculative activities in the housing market, Beijing's government implemented cooling measures in 2010 to restrict the number of units that residents/non-residents could purchase. Specifically, a local household in Beijing (who has a Beijing household *hukou*[8]) is not allowed to purchase residential properties if they already own two housing units in Beijing. Non-local households are not allowed to purchase residential properties in Beijing unless they have been working and paying taxes and social security in Beijing for at least five consecutive years.[9] Home buyers in Beijing can either buy new houses from the developers or second-hand houses from home owners. Second-hand housing transactions account for a large share of total housing transactions in Beijing because new developments are quite limited due to land supply constraints. Thus, in this paper, we focus on second-hand housing purchases.

Figure 3 introduces the typical procedures for second-hand housing property transactions in Beijing. First, a potential buyer contacts one or more real estate agents and communicates their housing preferences. Next, the agent(s) helps the buyer select a few candidate properties and conducts the showings. If the buyer is interested in a shown unit, the agent helps the buyer to arrange a meeting with the seller; this meeting is usually within a week or, in a hot real estate market, even the next day. During the meeting, the buyer and seller negotiate the price and the agent observes. If both parties agree on the price, the agent immediately prepares the contract, and the buyer and seller sign the contract on site. After signing the contract, the buyer pays the earnest money, which usually ranges from 10,000 *yuan* to 100,000 *yuan*, depending on the transaction price and the market. Then, it takes approximately two weeks to register the transaction in the online system of the Beijing Municipal Commission of Housing and Urban-Rural Development,

[8] A *hukou* is recorded in a government system of household registration required by law in mainland China and determines where citizens are allowed to live. *hukou* entitles the households with the access to local resources, such as hospitals, schools, and the eligibility to purchase a home in cities like Beijing.

[9] http://www.bjjs.gov.cn/portals/0/2016zhuanti/newbjgfzn/index.html

that is, the government agency monitoring housing transactions. Our data provides clear information on the exact date the buyer and seller negotiate the price and sign the contract. Notably, we could not observe if the negotiation failed from the data.

3 Data Sources

3.1 Air Pollution Data

Since 2008, the five U.S. Embassy and Consulates in China have measured and publicized the hourly reading of $PM_{2.5}$ in Beijing, Shanghai, Guangzhou, Chengdu, and Shenyang. We measure air pollution by using the hourly PM $_{2.5}$ readings published by the U.S. Embassy in Beijing. Specifically, we calculate the average of the PM $_{2.5}$ in a day as a proxy for the daily pollution level.

Another source of air pollution data is from the official air quality index (AQI) data released by the Ministry of Environmental Protection (MEP). In 2014, the MEP began to report the new measurement of AQI on its website for 153 cities in China; Beijing is one of those cities.[10] The levels of air pollution are also provided by the reported AQI. In China, air quality levels are classified into six categories: excellent, good, lightly polluted, moderately polluted, heavily polluted, and severely polluted. The corresponding AQI cutoff points are 50, 100, 150, 200, and 300, respectively.

We could potentially use the daily AQI as a measurement of air pollution in this paper. Nonetheless, a potential concern about the official AQI data is that the local government may manipulate it. As a pollution abatement effort, the air quality of a city is now as-

[10]Since 2001, the MEP has been publishing daily air pollution data on its website. Before 2012, the air pollution index (API), rather than the AQI, was reported on the website. The API is a composite index measuring air quality based on a city's concentration levels of sulfur dioxide (SO_2), nitrogen dioxide (NO_2), and particulate matter 10 (PM_{10}). A major difference between API and AQI is that AQI considers the concentration level of $PM_{2.5}$, which is one of the major pollutants in many cities that has caused the public's increasing concern. In addition, the AQI also incorporates the concentration levels of ozone (O_3) and carbon monoxide (CO) in the index. Please refer to $http://www.cnemc.cn/publish/106/news/news_25941.html$ for the new ambient air quality standards (GB3095-2012).

sociated with the promotion of local government officials. Therefore, this promotion opportunity may provide incentives for government officials to manipulate the reported air pollution data. By using the daily data of the API (Chen et al., 2012) we find evidence of downward manipulation at the cutoff point (i.e., 100)—the threshold for defining a "blue-sky day." Although no recent evidence exists about whether the newly adopted AQI is also flawed because of data manipulation, we use the $PM_{2.5}$ measure for the main results and conduct a supplementary analysis using AQI measures as robustness checks.

Notably, although the $PM_{2.5}$ is the major pollutant in certain cities, the $PM_{2.5}$ data cannot be directly compared with the AQI data by levels because the AQI is a composite index composed of six pollutants. Therefore, it is not sensible to create dummy variables for $PM_{2.5}$ levels based on the classification method of the AQI levels. To mitigate the concern about the comparability of the AQI and $PM_{2.5}$ categories, we adopt the cutoffs of $PM_{2.5}$ from the Technical Regulation on Ambient Air Quality Index published by the MEP in 2012. These cutoffs define the individual AQI, that is, the major input variables to calculate the AQI. Thus, we create dummy variables for the cutoff points of $PM_{2.5}$ at 35, 75, 115, 150, 250, and 350, resulting in seven dummy variables (including the omitted category) that represent the pollution levels.[11]

Figure 1 plots the distribution of the $PM_{2.5}$ and AQI based on category during our sample period, namely, 2014 and 2015. During those two years, Beijing had 43 days with $PM_{2.5}$ levels above 250 (29 days with AQI above 300), described as "hazardous" by the AQI definition. The distribution provides sufficient variation to examine the effect of severe air pollution on housing transactions.

3.2 Housing Transaction Data

We collect second-hand housing transaction data from one of the largest housing brokerage firms in Beijing. The sample covers transactions of second-hand housing units

[11]Please refer to Table 1 of the Technical Regulation on Ambient Air Quality Index available at http://210.72.1.216:8080/gzaqi/Document/aqijsgd.pdf.

from January 2014 to December 2015, with detailed information on the transaction prices, housing attributes, and a few demographic variables of the buyers and sellers, including their age, gender, and birth place. As mentioned in the previous section, a critical feature of the second-hand housing transactions is that the date the buyer and seller negotiate final price is predetermined, which is very unlikely to be affected by the air pollution level on the negotiation day. If the buyer and seller agree on the negotiated price, they sign the contract on site. Fortunately, the housing transaction data records the exact day the two sides negotiate and sign the contract, which allows us to understand the effect of air pollution on that day on the transaction price and volume.

Table 1 reports the summary statistics of the key housing attributes. The transaction price within our sample period is on average 2.98 million *yuan*. The average price per square meter is 37,003 *yuan*. We also have detailed housing characteristics of the transacted units, including size, floor level, facing, type of building, and distance to the central business district, calculated by the authors.

4 Hypotheses and Identification Strategy

4.1 Rational Predictions and Hypotheses

Standard economic theories predict that a rational agent in the housing market is not affected by weather or air quality of a single day. Because all the housing market participants in Beijing have lived in Beijing for a long time, due to the housing purchase restrictions (at least several years), they should not change their belief about the air quality in Beijing based on one day's severe air pollution. Hence, standard economic theories predict that the air quality or pollution level of the transaction day has no effect on the transaction price and volume.

By contrast, as demonstrated in the literature(Busse et al., 2015; Chang et al.; Conlin et al., 2007), very short-term exogenous shocks such as air pollution and weather have

been found to change people's decisions and behaviors due to different reasons. Although the decision of purchasing a house is more substantial, we suspect that similar mechanisms may still be at play in the housing market. Hence, we form our first hypothesis

Hypothesis 1. *The air pollution level on a particular day affects buyers' willingness to pay (WTP) and sellers' willingness to accept (WTA) and changes the market outcome.*

The second-hand housing market is a bilateral market based on the bargaining between (potential) buyers and sellers; thus, the market outcome can be further divided into two aspects: price and quantity. Figure 4 shows the relation between the possible market outcomes and possible underlying WTP and WTA changes. In particular, we can infer the changes in the WTP and WTA, although they are not directly observable. For example, an increase in both price and volume implies an increment in the WTP. With these predictions, we form a more testable hypothesis, compared with hypothesis one, about the transaction price and volume.

Hypothesis 2. *The air pollution level on a particular day affects either the observed transaction price or volume or both.*

4.2 Identification Strategy

In this research, we follow the standard hedonic pricing approach, where we regress housing transaction price (per square meter) on the hedonic housing attributes, community fixed effects, year-by-month fixed effects, weather controls, dummy variable for national holidays, and day-of-the-week fixed effect. Our core explanatory variable is the reported $PM_{2.5}$ at the daily level, which enters the following equation as a continuous

variable. The main regression equation is as follows:

$$\begin{aligned} UnitPrice_{i,j,t} =& Constant + \beta PM_{2.5_t} + \lambda_1 Weather_t + \lambda_2 Hedonic_j \\ &+ Community_i + Month_t + Holiday_t + DOW_t + \epsilon_{i,j,t} \end{aligned} \tag{1}$$

where $UnitPrice_{i,j,t}$ is the per square meter transaction price of community i housing unit j sold on day t. $PM_{2.5_t}$ measures the air pollution on the day of the negotiation. $Weather_t$ controls for weather on day t, including temperature, wind speed, dew point, and dummy variables for fog, snow, rain, and thunder.[12] $Hedonic_j$ includes all the characteristics of housing unit j. In the full specification, the community fixed effects, year-by-month fixed effects, housing characteristics, dummy variable for national holidays, and day-of-the-week fixed effects have been controlled for. We adopt the robust standard error two-way clustering at the community and date levels.

In addition to using the continuous measurement of $PM_{2.5}$, we also adopt the categorical measure of $PM_{2.5}$ in seven levels (at the corresponding cutoff points: 35, 75, 115, 150, 250, and 350, as explained in Section 3.1) to overcome the possible nonlinear effect of air pollution on housing transactions in the following specification:

$$\begin{aligned} UnitPrice_{i,j,t} =& Constant + \sum_{n=2}^{7} \beta_n PM_{2.5_{n,t}} + \lambda_1 Weather_t + \lambda_2 Hedonic_j \\ &+ Community_i + Month_t + Holiday_t + DOW_t + \epsilon_{i,j,t} \end{aligned} \tag{2}$$

where $PM_{2.5_{n,t}}$ stands for dummy variables for different levels of $PM_{2.5}$, and level 1 is used as the omitted category. The rest of the notations are the same as in Equation 1.

We are interested in the coefficients of $PM_{2.5}$: the effect of the current day's air pollution level on the housing transaction price. From a rational point of view, the air pollution

[12]The weather data are from the National Climatic Data Center under the US National Oceanic and Atmospheric Administration (NOAA), which provides rich daily weather information at the monitor station level.

level on the day of the transaction should not affect the transaction price. Thus, we should expect no significance of any pollution coefficients—after controlling for the fixed effects and other variables—if market participants are fully rational agents.

4.3 Instrumental Variable Estimation

Although we believe that air pollution can be an exogenous shock in a very short-term reaction, to address possible concerns over endogeneity problems, we also conduct IV estimations for our main results. To generate the instrumental variables, we employ the approach of thermal inversion. Thermal inversion (i.e., temperature inversion) refers to the meteorological phenomenon that the temperature at a higher altitude is higher than the temperature at a lower altitude. Smog or air pollution is one of the major consequences of thermal inversion, and smog is impacted by the inversion layer because it is—in essence— capped when a warm air mass moves over an area. This phenomenon occurs because the warmer air layer sits over a city and prevents the normal mixing of cooler, denser air. The result is stagnant air, and over time, the lack of mixing traps the pollutants under the inversion and significant amounts of smog develop. Because thermal inversion is a pure meteorological phenomenon, we can be confident in the validity of thermal inversion as the instrumental variable.

For greater detail, we obtained the NOAA atmospheric data.[13] Among all the recorded data in the NOAA dataset, the temperature and wind variables are of particular interest. We use the pressure information to represent the different layers and the corresponding

[13]NOAA measures the temperature, atmospheric pressure, wind speed, wind directions, and several other variables. The atmospheric data was measured twice per day at 12 am and 12 pm UTC, that is, 8 am and 8 pm Beijing time

temperature readings at different layers to construct the thermal inversion data.[14]

$$PM_{2.5_t} = \gamma Thermal\ Inversion_t + \delta Wind\ Speed_t + \phi Wind\ Direction_t + \epsilon_t \tag{3}$$

Hence, in the first stage of the IV regression, we included the temperature differences constructed at different layers (subscript m and see footnote for details), wind speed, wind direction, and dummy variables that indicate whether the thermal inversion occurs at a particular layer. We also included the following: the squared and cubed temperature differences, wind speed, and their lagged terms.[15]

5 Main Findings

Table 2 shows the impact of air pollution on the day of the negotiation on the transaction prices (per *sqm*). In all the reported regressions, we control for year-by-month fixed effects, community fixed effects, weather, and housing unit characteristics. Some of the specifications also control for day-of-the-week fixed effects and the holiday dummy variable. From the most complete specification (column 2 of Table 2), we observe that the coefficient of $PM_{2.5}$ (divided by 100 for the convenience of reporting) is positive and signifi-

[14]The reason we use different levels of pressure to represent the layers in the atmosphere is that pressure is the main cause of airflow. In addition, the relationship between altitude and pressure is quite linear. The pressure levels used are 1000, 925, 850, 700, 500, 400, 300, 250, 200, and 150 mbar.

[15]The detailed first stage specification is as the following:

$$\begin{aligned} PM_{2.5_t} = & \sum_{t=0}^{-2}\sum_{m=0}^{4} \gamma_{1\cdot m,t} TempDiff_{m,t} + \sum_{t=0}^{-2}\sum_{m=0}^{4} \gamma_{2\cdot m,t} TempDiff^2_{m,t} + \sum_{t=0}^{-2}\sum_{m=0}^{4} \gamma_{3\cdot m,t} TempDiff^3_{m,t} \\ & + \sum_{t=0}^{-2} \delta_{1\cdot t} WindSpd_t + \sum_{t=0}^{-2} \delta_{2\cdot t} WindSpd_t^2 + \sum_{t=0}^{-2} \delta_{3\cdot t} WindSpd_t^3 \\ & + \sum_{t=0}^{-2} \phi_t WindDir_t + \sum_{t=0}^{-2}\sum_{m=0}^{4} Inversion_{m,t} + \xi_t \end{aligned}$$

where t represents the layer number and m represents layer number from low altitude to high altitude. Temperature differences ($TempDiff$) are calculated by subtracting the temperature of the lower layer from the temperature of the layer one level above. Wind speeds ($WindSpd$) are reported in the NOAA data. Wind directions ($WindDir$) are four dummy variables representing the north, south, east, and west. $Inversion$ is a dummy variable that takes the value 1 if a thermal inversion occurs at a certain layer.

cant at the 0.01 level. Specifically, an increase of $PM_{2.5}$ by 100 on the day of the negotiation leads to an approximately 0.19% increase in the per *sqm* transaction price. Using average transaction price and volume on a typical day, the calculated total increase is about 1.7 million *yuan* which is an economically significant amount. Column 3 reports the two-stage least square estimation where we use thermal inversion, wind speed, and wind direction to instrument for daily $PM_{2.5}$. The coefficient estimate using 2SLS is slightly larger compared with the OLS estimate in column 2. The significance level remains unchanged. One potential problem with the 2SLS estimation is that the critical value of the first stage F-statistic is not clear with two-way clustered standard errors (Cameron and Miller, 2015). Therefore, we report both the Cragg-Donald F-statistic (assuming i.i.d. standard errors) and Kleibergen and Paap F-statistic (for clustered errors) for the IV results. Additionally, due to the same reason, we take the 2SLS estimation as a robustness check and trust the OLS estimation with full specification as the main result. Given the average unit price and size of the transacted houses in Beijing, it translates into approximately 5,800 *yuan* or USD 893 (i.e., based on the exchange rate on December 2015, which is 12% of the yearly per capita disposable income in Beijing in 2015 (48,458 *yuan*).

We also report the estimation using the $PM_{2.5}$ levels as categorical variables in Table 2. The coefficients on $PM_{2.5}$ for all the levels (except level 5) are positive and significant at the 0.1 level. In addition, the magnitude of the coefficients increases with the pollution levels, indicating some nonlinear effect of pollution levels on housing transaction prices. The transaction prices on a severely polluted day ($PM_{2.5}$ level 7) are 0.7% higher than that of the days without pollution ($PM_{2.5}$ level 1), other things being equal. Given the average transaction price, as shown in Table 1,the coefficient translates into a monetary value of 20,882 *yuan* (USD 3,215). In summary, the result indicates that air pollution on the negotiation day increases the transaction price.

We conduct four robustness checks. First, we use the AQI data to replicate the results in Table 2, even though the AQI data may have been manipulated by the local govern-

ment and this might lead to biased estimates (Chen et al., 2012). The result is reported in Table A.1 and very similar to the ones using $PM_{2.5}$. Second, we exploit the cross-sectional variation of air pollution levels in Beijing by using monitoring station-level pollution data provided by the MEP. Beijing has 12 air pollution monitoring stations across its districts that report hourly AQI and $PM_{2.5}$ levels. We match each housing transaction to the AQI and $PM_{2.5}$ readings from the nearest monitoring station; thus, we can use the air pollution levels in different geographic areas on the same day. Table A.2 reports the robustness check using station-level air pollution measurements as the key independent variable. Again, a higher air pollution level is significantly associated with higher transacted prices on that day. We do not use the station-specific pollution measures in the main setting because the negotiation between buyers and sellers may not take place in the nearby area of the transacted property. Third, we also include 10- and 30-day lags of the $PM_{2.5}$ and AQI index in the regression equation as additional controls and obtain similar results (Table A.3). Fourth, we adopt a polynomial distributed lag model, which can mitigate the concern of multicollinearity across the lag terms of air pollution (Almon).[16] The results are presented in Figure B.1. For the distributed lag model using 10-day lags (subfigures (a) and (d)), we observe a positive and significant coefficient for day 0, and this is consistent with the previous main findings. In addition, the lagged air pollution does not significantly affect transaction prices. However, we observe a significant current day effect and a significant lagged effect when we extend the lag structure to 20- and 30-day lags. One possible reason for this phenomenon is that the air pollution on the day the house was

[16]The specification of the distributed lag model is as follows:

$$\begin{aligned} UnitPrice_{i,j,t} =& Constant + \sum_{i=0}^{k} \beta_i PM_{2.5_{t-i}} + \lambda_1 Weather_t + \lambda_2 Hedonic_j \\ &+ Community_i + Month_t + Holiday_t + DOW_t + \epsilon_{i,j,t} \end{aligned}$$

For each β_i, it is specified as a polynomial function of time with order q. For example, if $q = 3$,

$$\beta_i = \gamma_0 + \gamma_1 i + \gamma_2 i^2 + \gamma_3 i^3$$

In our robustness check, we present the results for $q = 3$ and $q = 4$ and for the 10-, 20-, and 30-day lags. Please refer to Barwick et al. (2017) for additional technical details.

shown might also affect transaction outcomes, and those occur a number of days before the day the contract is signed. However, we cannot directly test this hypothesis because we have no information on the exact date the house was shown.

In addition to transaction price, we also conduct an analysis on daily transaction volume by aggregating the number of transactions and run the following regression using the continuous measure of $PM_{2.5}$,

$$\begin{aligned} Volume_t =& Constant + \beta PM_{2.5_t} + \lambda Weather_t \\ &+ Month_t + Holiday_t + DOW_t + \epsilon_t \end{aligned} \tag{4}$$

and the categorical levels of $PM_{2.5}$ as follows,

$$\begin{aligned} Volume_t =& Constant + \sum_{n=2}^{7} \beta_n PM_{2.5_{n,t}} + \lambda Weather_t \\ &+ Month_t + Holiday_t + DOW_t + \epsilon_t \end{aligned} \tag{5}$$

where $Volume_t$ stands for the transaction volume on day t. The main regressors are $PM_{2.5}$ as the continuous variable and in levels expressed as categorical variables. We also control for weather variables, year-by-month fixed effects, day-of-the-week fixed effects, and holiday dummy. In addition, we also include a 30-day lagged $PM_{2.5}$ in different specifications, respectively. Robust standard errors are adopted for all the regressions. In addition to the OLS estimates, we report an IV estimation that uses the same IV as the transaction price analysis.

Table 3 shows the results. Columns 1 and 2 use continuous $PM_{2.5}$ data with column 2 controlling for the 30-day lagged terms. Column 3 reports estimates from the 2SLS estimation, and column 4 uses categorical $PM_{2.5}$ data. The coefficients are positive in all specifications, indicating higher transaction volumes on polluted days. However, the estimated coefficients are not statistically significant in some of the specifications (column

3). Therefore, the conservative conclusion from this table is that transaction volume does not decrease on more-polluted days.

Given that we observe an increase in transaction price and a non-decrease in transaction volume on polluted days, we can infer that the buyers' WTP is significantly higher on more-polluted days, based on the nine possible outcomes in Figure 4. Regarding sellers' WTA, we cannot reach a definite conclusion with this evidence. In the next section, we will show that such results cannot be reconciled with rational explanations. In Section 7, we further demonstrate that our empirical finding is consistent with some behavioral theories, such as salience and projection bias.

6 Rational Explanations

In the previous section, we have shown that the transaction prices are significantly higher, and volumes do not decrease (if not higher) when air pollution is present on the day of the negotiation. In this section, we discuss possible rational explanations.

Explanation one: selection

One obvious explanation for the positive association between air pollution and transaction prices is selection. For example, buyers who sign a contract on polluted days may place a higher value on home ownership in Beijing, because going outside on a polluted day would increase their exposure to pollution. In this case, the total transaction volume on polluted days would decline because only buyers with a higher valuation of home ownership in Beijing would be selected for the sample. However, as shown in Table 3, none of the coefficients of the $PM_{2.5}$ levels are significantly negative across the specifications, which is against the selection hypothesis.

Explanation two: cognitive function changes induced by pollution

Another explanation is that the air pollution affects individuals' cognitive abilities, which then affects the negotiation process and the transaction price. For example, Chen

et al. (2016) observed that exposure to air pollution may negatively affect individuals' cognitive ability of mathematics. Stafford (2015) suggests that indoor air quality affects students' academic performance. Other papers, such as Graff Zivin and Neidell (2012) and He et al. (2016), suggest that air pollution may affect workers' productivity. If air pollution affects the negotiation process of buyer and seller by impairing their cognitive abilities or lowering their productivity during the negotiation, rational theories would suggest price or volume change in the transactions.

To rule out this hypothesis, we identify whether a buyer is a Beijing local resident from the first two digits of their national identity card,[17] and separately estimate the effect of air pollution on transaction prices for local and non-local buyers. If the aforementioned explanation holds, we would observe that air pollution has similar effects on local and non-local buyers. Table 4 shows the estimation for local and non-local buyers in separate sub-samples using OLS estimation (columns 1 and 2) and IV estimation (columns 3 and 4). Air pollution significantly increases the transacted price for non-local buyers but has no effect on local buyers. The results are very similar if lagged pollution measures have been controlled for (Table A.4 and Table A.5). Figure 5 (summarized from the estimation results in Table A.6, column 4) reports the impact of air pollution (in levels) on transaction price only for local buyers. Contrasting with the main results, none of the coefficients of air pollution are significant, suggesting that air pollution does not affect the subgroup of local buyers. By contrast, Figure 6 (summarized from the estimation results in Table A.6, column 2) shows the impact of air pollution (in levels) on transaction price for non-local buyers. Different from the results on local buyers, the positive effect of $PM_{2.5}$ levels has statistical significance at the 0.01 level for non-local buyers. The heterogeneous impact of air pollution in transaction volumes is shown in Table 5. The OLS results indicate that non-local buyers purchase more housing units on polluted days, whereas the number of purchased houses are not affected by air pollution in the local buyer group. The results are

[17] The first two digits represent the birth province of a Chinese citizen.

also similar if we use the AQI as the main regressor (Table A.7). None of the coefficients are significant in the IV estimations. However, the estimated coefficients have different signs for local and non-local buyers. These results suggest that it is unlikely that the observed positive effect in the main result is driven by cognitive functioning changes induced by air pollution.

Another possible argument is that air pollution has different effects on local and non-local buyers because the durations of their exposure are different . Although we cannot test this alternative explanation directly with our empirical data, it is highly unlikely to be true for the following reason. Given the restriction on housing purchases in Beijing, a buyer must have either Beijing *hukou* or five consecutive years working experience in Beijing to be eligible to make a purchase. For Beijing *hukou*, this can only be obtained through limited channels. A majority of non-local people who obtain Beijing *hukou* each year are those graduates who receive their college degrees from one of the cities' universities. Hence, the local and non-local buyers in our sample have been exposed to air pollution for a sufficiently long time, and it is unlikely that air pollution affects them differently.

7 Behavioral Explanation

In this section, we discuss two behavioral explanations consistent with our empirical results. Under some weak assumptions, salience theory shows that buyers shift their attention from housing price to quality; thus, they are willing to pay more. Projection bias predicts that buyers would be willing to pay a higher price if they over predict the extent to which a self-owned house can protect them on polluted days, but this prediction requires stronger assumptions.

With either explanation, it is important to know the market participants' choice sets. It is reasonable to argue that people who enter the last stage of buying a house are deter-

mined to work and live in Beijing. That is, at least in the very short run, moving to another city is not in their choice sets. This argument is also consistent with the mental accounting and narrow bracketing literature (Kahneman, 2003; Read et al., 1999; Thaler, 1999). It is worth noting that choice set or choice context was also important in previous studies. For example, Busse et al. (2015) discussed the effects of weather on the purchase of convertible cars. Thus, the implicitly assumed alternatives in the choice set are non-convertible cars.

7.1 Salience of Living Quality

Salience, in the context of economic decision-making, argues that decision-makers pay attention to a certain feature of a good. Hence, the feature receives disproportionate weight in the decision-making process. The idea of salience was formulated in Bordalo et al. (2012, 2013a,b); Kőszegi and Szeidl (2012) and empirical evidence has been found to support the salience thinking (Dessaint and Matray, 2017).

To demonstrate that salience theory is consistent with our empirical results, we adopt a simple example formulation from Bordalo et al. (2013b). The most important component of the formulation is the salience function σ that has the following functional form:

$$\sigma(a_k, \bar{a}) = \frac{|a_k - \bar{a}|}{a_k + \bar{a}} \tag{6}$$

where a_k represents the attribute of good k and $\bar{a}$ represents the attribute of the average or reference good. In our analysis, we assume the simplest case where housing units only have two attributes: quality(q, including the air quality consideration) and price(p).

$$u_k^s = \begin{cases} \frac{2}{1+\delta} q_k - \frac{2\delta}{1+\delta} p_k & \text{if } \sigma(q_k, \bar{q}) > \sigma(p_k, \bar{p}) \\ \frac{2\delta}{1+\delta} q_k - \frac{2}{1+\delta} p_k & \text{if } \sigma(q_k, \bar{q}) < \sigma(p_k, \bar{p}) \\ q_k - p_k & \text{if } \sigma(q_k, \bar{q}) = \sigma(p_k, \bar{p}) \end{cases} \tag{7}$$

u_k^s gives the utility of living in house k under salience thinking. As noted in Bordalo et al. (2013b), $\delta \in (0, 1]$ and is decreasing in the severity of salient thinking. In the context of our study, q stands for the living quality, and p stands for the corresponding price the buyer must pay . Consider the case in which consumers' choice context has two elements: buying the house and staying with the status quo. Each choice has two attributes (q_{buy}, p_{buy}) and (q_{rent}, p_{rent})[18]. We use the subscript "$rent$" to denote the status quo for convenience, but the salience prediction is general as long as $q_{buy} > q_{rent}$ and $p_{buy} > p_{rent}$[19]. The reference good is thus $(\bar{q}, \bar{p})$ where $\bar{q} = \frac{q_{buy}+q_{rent}}{2}$ and $\bar{p} = \frac{p_{buy}+p_{rent}}{2}$. The weak assumption that we impose is that the air pollution induces a negative shock of the same magnitude–Δ–to both q_{buy} and q_{rent}[20], reducing the quality of living for housing owners and renters. Using the salience function in Equation 6, it is easy to show that air pollution increases the salience of living quality relative to price[21]. Then, following Bordalo et al. (2013b), buying a house becomes more attractive when q_{buy} and q_{rent} both experience a negative shock. When quality is salient, buyers overvalue quality relative to price, but they overvalue the quality of buying a house more. The essence of this explanation is that air pollution decreases the living quality of buying and renting; thus, the living quality between buying and renting becomes proportionally larger and the absolute difference remains unchanged. This increased proportional difference between buying and renting increases the salience of living quality relative to price; thus, people weigh living quality disproportionately more relative to price. In a case where decision-makers only consider buying the negotiated house or continuing to rent, the discussed prediction is true under fairly weak assumptions. To quote Bordalo et al. (2013b), "...this prediction depends only

[18]We argue that the choice context has only these two elements but the analysis can be extended to a case in which buyers can compare different houses in Beijing

[19]p_{buy} is *not* the price at which the house is sold but the user cost as usually defined in the housing literature. p_{rent} is the cost of rent. We assume that $q_{buy} > q_{rent}$ because the utility that people derive from their own houses is usually higher than their rented houses due to reasons such as decoration.

[20]In the case where the negative shock is not the same for owners and renters, we must further assume that $\Delta_{buy} < \Delta_{rent}$. This is a plausible assumption given that owner-occupied houses are usually of better quality than rented properties. We only consider that case where $\Delta_{buy} = \Delta_{rent} = \Delta$, but the same conclusion applies when $\Delta_{buy} < \Delta_{rent}$.

[21]$\sigma_{pollution} = \frac{|q_{buy}-\Delta-(\bar{q}-\Delta)|}{q_{buy}-\Delta+(\bar{q}-\Delta)} = \frac{|q_{buy}-\bar{q}|}{q_{buy}+\bar{q}-2\Delta} > \frac{|q_{buy}-\bar{q}|}{q_{buy}+\bar{q}} = \sigma_{clear}$

on (i) prices and (ii) the quality ranking of the two goods."

Based on the discussion in this subsection, the salience explanation generates predictions consistent with our empirical results:

1. Air pollution decreases living quality and draws attention to the quality attribute (relative to price). Therefore, buyers would be willing to pay higher prices.

2. If current homeowners are upgrading, they are less affected by air pollution shock because the living condition differences between their new and current houses are smaller.

3. Air pollution draws attention to living quality; thus, more people would be thinking about improving their living conditions.

Our main result and the heterogeneous analyses are consistent with predictions 1 and 2. In particular, we observe an increased transaction price and non-decreasing volume that indicate an increase in buyers' WTP. Our heterogeneous analyses help determine the group of people likely to be first-time home buyers. Our empirical results show that this group of people is most affected by salience thinking. In addition, our analysis of the sentiment data (i.e. search engine and website visits) in Section 7.3 is also consistent with prediction (3) of salience theory.

In the following subsection we provide another behavioral explanation: projection bias. We further show that projection bias is also consistent with our empirical results but under stronger assumptions.

7.2 Projection Bias over Living Quality

Projection bias refers to the tendency of over-predicting the degree to which one's future tastes will resemble one's current tastes. Unlike most studies, in this study, we observe and analyze a bilateral bargaining market. We start from the buyer side by illustrating

how projection bias could affect their WTP. As shown in Loewenstein et al. (2003), projection bias can be expressed in the form of

$$\tilde{u}(c, s|s') = (1 - \alpha)u(c, s) + \alpha u(c, s') \tag{8}$$

where $u(\cdot)$ is a state-dependent utility function whose value is determined by consumption c and the state of the world s. The cause of projection bias is that when people evaluate utility from a *future* consumption, they are also influenced by the current state of the world s'. Relating to the housing market in this study, negotiations and transactions are made on day 0, but buyers will only receive consumption utility starting from day 1, when they move in. As previously discussed, people should not change their information about the local pollution level based on their observation of the pollution level on a single day; thus, pollution in day 0 should not affect their predictions of pollution level in day $1, 2, \ldots, T$.

Housing, unlike many other consumption goods, lasts for a very long time. Buyers' WTP for an owned house are determined as follows.

$$WTP_0 = \tilde{U}_0(\tilde{u}_1, \tilde{u}_2, \ldots, \tilde{u}_T|s_0) \tag{9}$$

where $\tilde{U}_0$ is the total discounted consumption utility the buyer receives from the housing unit over T days evaluated at day 0 [22]. s_0 is the pollution level on day 0, when the transaction is made or attempted. Further assume that the discount factor is δ and number of days between the transaction and move-in date (number of days between day 0 and day 1) is R. Substitute Equation 8 into Equation 9, we have

$$WTP_0^B = \sum_{t=1}^{T} \delta^{R+t-1}[(1 - \alpha)u^B(c, s_t) + \alpha u^B(c, s_0)] \tag{10}$$

[22] A resale price can also be considered under this framework. However, assuming for a long-lived representative agent would be the same

Similar to the analysis with salience theory, we assume the potential buyers' choice set has two options: to purchase a house or remain a renter[23]. Notably, this assumption is plausible because those who would like to leave Beijing wouldn't enter the negotiation stage. Conditional on living in Beijing, potential buyers only need to determine whether a price is acceptable to them. The WTP for a rental property can be written as:

$$WTP_0^R = \sum_{t=1}^{T} \delta^{R+t-1}[(1-\alpha)u^R(c, s_t) + \alpha u^R(c, s_0)] \tag{11}$$

On a clear day, for a marginal potential buyer, we have $WTP^B = WTP^R$. If we predict the empirical results with projection bias, it requires that the WTP^B is less affected than WTP^R. That is, self-owned houses are less affected by pollution compared with rental properties. Intuitively, this means that rental properties are less "resilient" to the negative shock caused by severe pollution. Although this is also plausible in Beijing's housing market, it is still a stronger assumption than the salience theory requires. In the next subsection, we provide further evidence for the salience theory.

7.3 Further Evidence and Discussion

In the previous section, we discussed the explanations based on rational choice theories. Our empirical results ruled out these rational explanations. Although we cannot rule out all possible rational explanations, we show that our empirical results can be explained by salience theory (with weak assumption) and projection bias (with stronger assumptions). As discussed, the degree of salience thinking and projection bias of first-time home buyers is supposed to be higher than experienced market participants because they are reminded of the importance of living quality by the heavy pollution. Other participants in the market, including experienced buyers and sellers, are less affected by this factor because they have already achieved home ownership.

[23]Suggested by our empirical analysis, we found that the effect mostly pertains to first-time home buyers; thus, we restrict our discussion to this subgroup.

Tables 6 to 8 provide heterogeneity tests of different groups of buyers that further support the projection bias hypothesis. Specially, we find that the effect of air pollution on transaction prices is positive and significant only for the following two subgroups of buyers: non-local buyers whose age is below the median (33 years old), as shown in Table 6; and non-local buyers whose purchased unit is below median size (75 square meters), as shown in Table 7. In addition, we find that air pollution does not have a significant effect on transaction prices for experienced home buyers, local or non-local, as shown in Table 8.[24] All these results suggest that the home buyers most affected by air pollution are likely to be first-time home buyers in Beijing.

In addition to the heterogeneous responses from the subgroups, we also provide other supplementary evidence using online searches and web click data. For example, we show that people pay more attention to housing on polluted days. Specifically, we collect the daily Baidu index, a similar product to Google Trend, on a few key words in Chinese related to home purchases, including (1)"Lianjia," the largest second-hand housing broker in Beijing; (2) "Buy House" (*mai fang*); and (3) "Soufun," the largest housing brokerage firm in China. In addition, we collect the number of visitors to the Soufun website with Beijing IP addresses on a daily basis. We run the following regression:

$$Index_t = Constant + \beta PM_{2.5_{n,t}} + \lambda Weather_t + Month_t + Holiday_t + DOW_t + \epsilon_t, \quad (12)$$

where $Index_t$ stands for the Baidu indices or Soufun web click data on day t. The main regressor is the continuous measurement of $PM_{2.5}$. We also control for weather variables, year-by-month fixed effect, day-of-the-week fixed effect, and holiday fixed effect. In addition, we also include 30-day lags of the $PM_{2.5}$ on the right-hand side of the equation. We adopt robust standard errors in the regressions.

As shown in Table A.8 (and Table A.9, for a robustness check using the AQI as the

[24]We identify the group of buyers as experienced buyers if they have ever appeared in our sample as a seller, or a buyer prior to the current purchase.

main regressor), people search for these housing-related keywords more on polluted days. They also visit the broker's website more.[25] These results support our argument that pollution reminds non-home owners of the importance of home ownership or, in the language of salience theory, the importance of living quality. Given the heterogeneous responses by different subgroups and the web click and visit results, we assert that air pollution-induced salience thinking is the most plausible explanation for our empirical results. These conclusions are also consistent with the predictions made by salience theory and suggest that the immediate effect of pollution on housing transactions can be different from its long-term effect.

8 Conclusion

In this paper, we provide novel evidence of salience thinking in the housing market. We find that an increase of the $PM_{2.5}$ by 100 on the day of the negotiation leads to an approximate 0.19% increase in the per unit transaction price in Beijing's second-hand housing market. One possible explanation is that people care more about indoor living quality on polluted days because they tend to remain indoors longer on those days. Thus, pollution induces salience thinking and shifts the decision so it is weighted more toward living quality. As predicted by the salience theory, this effect is more prominent for inexperienced market participants or first-time home buyers. Accordingly, we find that non-local home buyers, who are also young and buying small houses, are mostly subject to such salience thinking because they are likely to be first-time home buyers in Beijing transitioning from renters to home owners. We also provide an alternative behavioral explanation, namely, projection bias, that requires a stronger assumption but is also consistent with our empirical results under such an assumption.

[25] It is unlikely that our results are driven by additional online search activities on polluted days, as falsified by Qin and Zhu (2018), who examine the effect of air pollution by using a Baidu search index on emigration in Beijing and other prefecture cities in China and find that people search more for "emigration" on polluted days, but not other pollution-irrelevant keywords, such as "socks," "clothes," and "job-hunting."

Correctly predicting utility is critical in long-term, important decision-making processes such as purchasing a house. However, with our empirical evidence, we have demonstrated that people are vulnerable to the influences of many contextual factors. In this study, we observe that air pollution affects how much buyers focus on the quality or price of housing units. This finding echoes and differentiates our results from the findings of Chang et al., who found that air pollution affects how people value insurance policies. Additionally, other factors such as weather could potentially influence the valuation of future consumption (Busse et al., 2015; Conlin et al., 2007). Hence, such behavioral bias demands for certain policies to reduce its influence and subsequent regret induced by the mistakes. In the context of the housing market, our findings suggest that the existence of a time interval between price negotiation and signing the final contract may help buyers reduce the magnitude of such a bias. Moreover, real estate brokers may take advantage of this bias by rushing buyers and sellers to "close the deal" on the same day. Hence, regulations can be implemented that improve the housing market transaction process and reduce the regret incurred by market participants.

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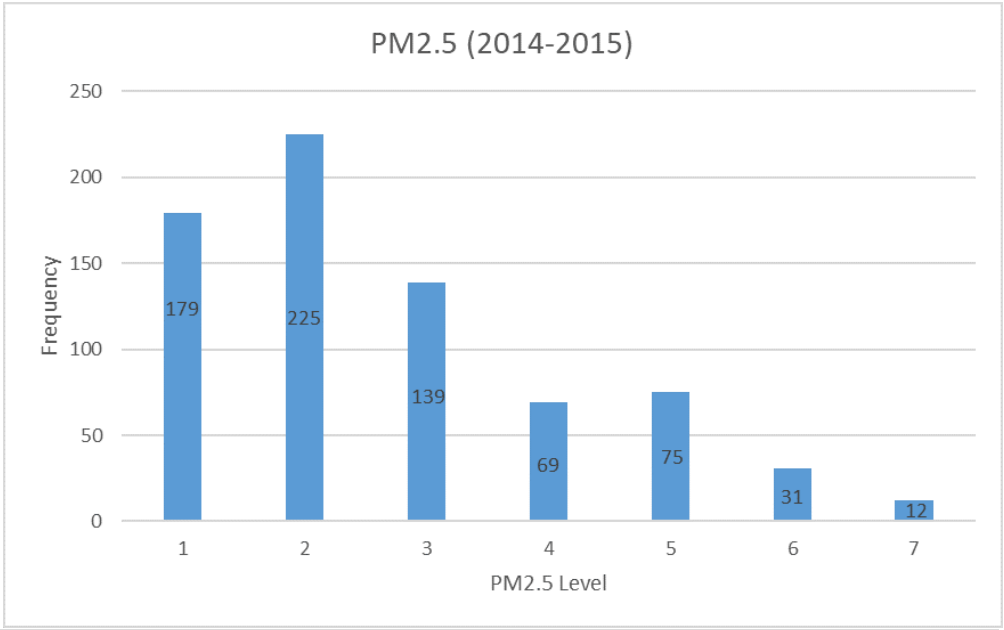
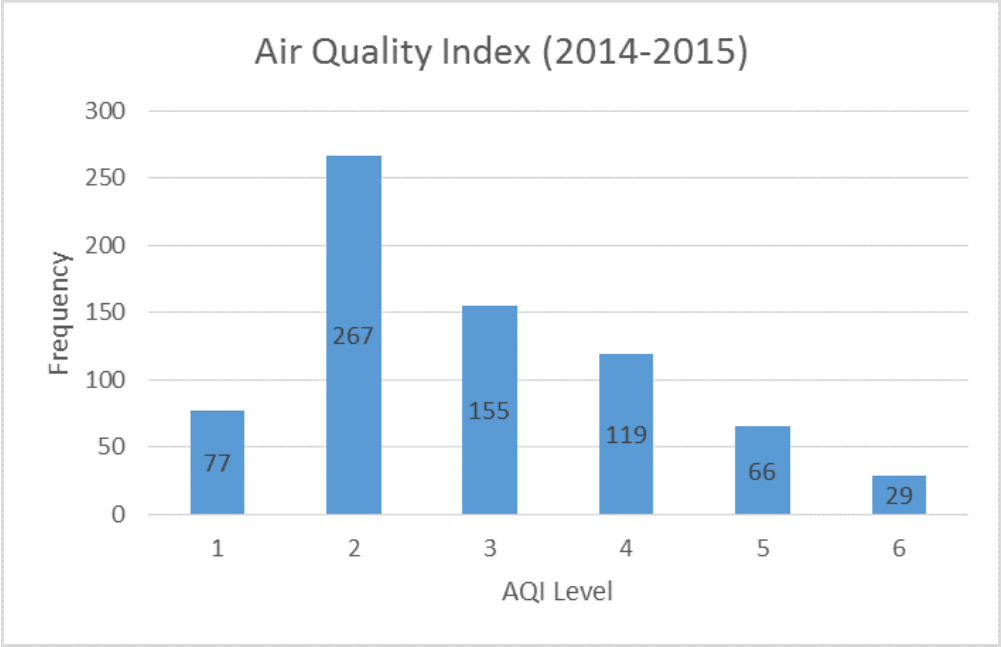
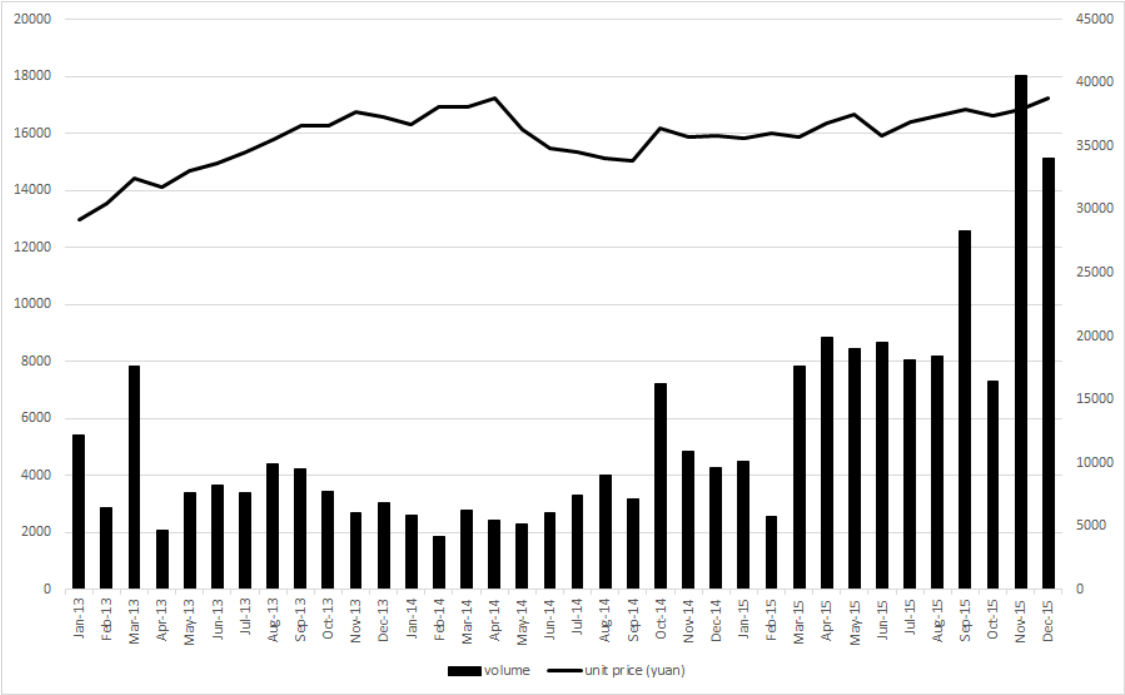
Figure 1: Air Quality in Beijing (2014-2015)





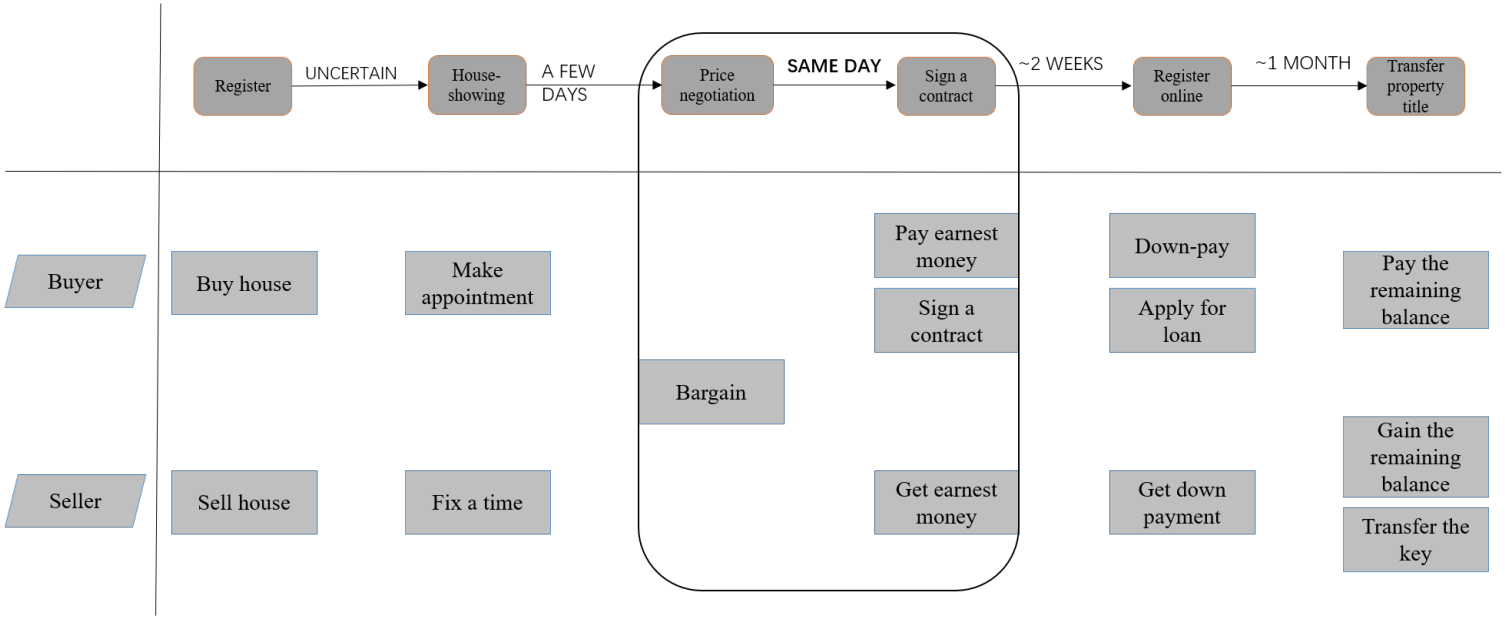
Data source: $PM_{2.5}$ data is from the U.S. Embassy in Beijing and AQI data is from Ministry of Environmental Protection (MEP).

Figure 2: Housing prices and transaction volume in Beijing (2014-2015)



Data source: authors' calculations from the housing brokerage firm.

Figure 3: Transaction Process of Second-hand Houses in Beijing

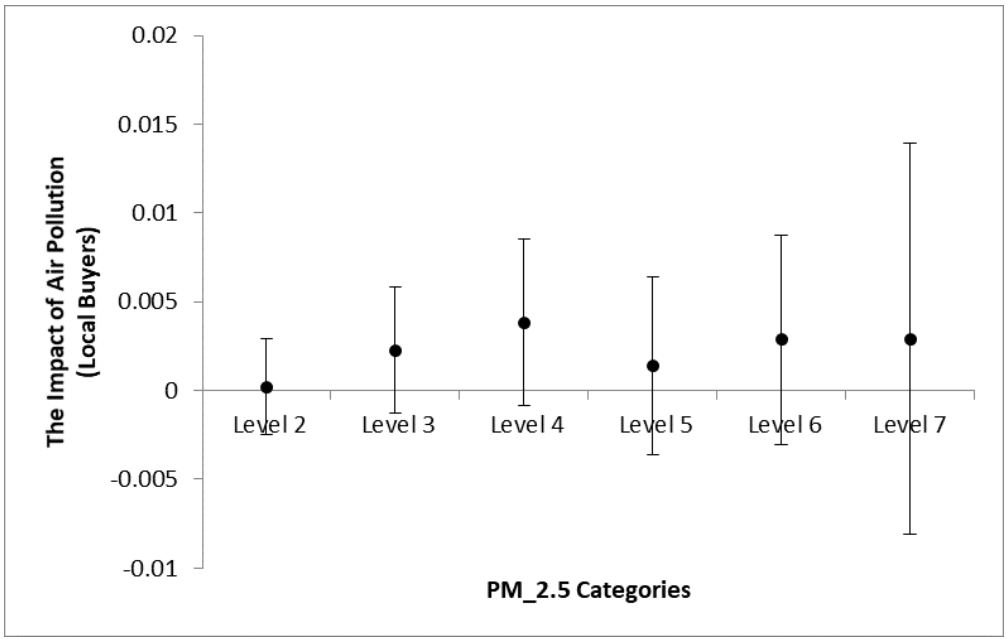


Note: Information collected by the authors from the housing brokerage firm.

Figure 4: Inferred WTP and WTA Changes Using Market Outcomes

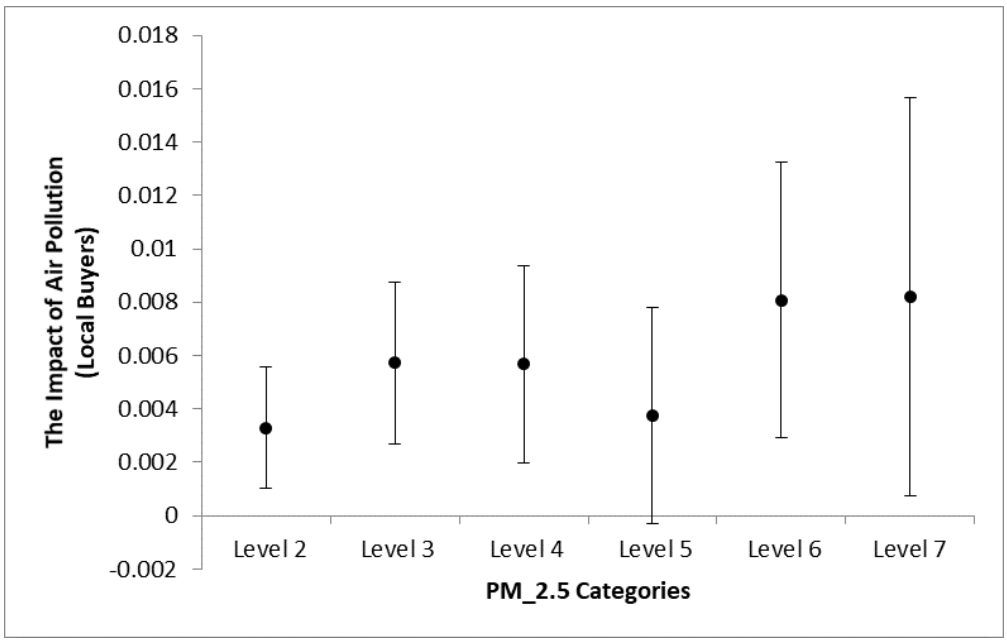
	$Price\uparrow$		$Price-$		$Price\downarrow$	
$Volume\uparrow$	$WTP\uparrow$	$WTA\updownarrow$	$WTP\uparrow$	$WTA\downarrow$	$WTP\updownarrow$	$WTA\downarrow$
$Volume-$	$WTP\uparrow$	$WTA\uparrow$	$WTP-$	$WTA-$	$WTP\downarrow$	$WTA\downarrow$
$Volume\downarrow$	$WTP\updownarrow$	$WTA\uparrow$	$WTP\downarrow$	$WTA\uparrow$	$WTP\downarrow$	$WTA\updownarrow$

Figure 5: The Impact of Air Pollution on Unit Price (Local Buyers)



Note: Regression coefficients with 95% confidence interval.

Figure 6: The Impact of Air Pollution on Unit Price (Non-Local Buyers)



Note: Regression coefficients with 95% confidence interval.

Table 1: Summary Statistics

Sample period: 2014.01.01-2015.12.31; 5515 communities						
Variable	Explanation	Observations	Mean	Std. Dev.	Min	Max
$PM_{2.5}$	$PM_{2.5}$	148732	93.983	83.863	5.2	537.25
dealprice	Transaction price (yuan)	148732	2983212	1736097	111200	4.4E+07
sqmprice	Unit price (yuan)	148732	37002.75	14483.74	5221.66	149275
volume	Transaction volume (unit)	720	206.572	184.670	1	1530
bedroom	Number of bedrooms	148720	2.011	0.738	1	4
area	Area (sqm)	148732	82.602	34.665	10	504
currentfloor	Floor	148732	7.255	5.759	1	40
green_lvl	Greening rate	129776	0.332	0.070	0.04	0.9
center	Distance to CBD (meter)	134875	13348.140	7869.734	882	70147
face1	North-South exposure	148732	0.479	0.500	0	1
face2	Face south	148732	0.255	0.436	0	1
face3	Other facing	148732	0.267	0.442	0	1
type_build 1	Slab-type apartment	148732	0.569	0.495	0	1
type_build 2	Tower block	148732	0.179	0.384	0	1
type_build 3	Combined type	148732	0.251	0.434	0	1
type_house1	Apartment	148732	0.021	0.144	0	1
type_house2	Ordinary residence	148732	0.979	0.144	0	1
only_	Only residence	142018	0.705	0.456	0	1
full_	Resold within 5 years	123672	0.919	0.273	0	1

Notes: 1. $PM_{2.5}$ data is collected from the U.S. Embassy in Beijing.
2. Housing transaction data is collected from a housing brokerage firm in Beijing.

Table 2: The Impact of Air Pollution ($PM_{2.5}$) on Transacted Prices (*per sqm*)

Variables	OLS Ln(Unit Price)	OLS Ln(Unit Price)	2SLS Ln(Unit Price)	OLS Ln(Unit Price)	OLS Ln(Unit Price)
$PM_{2.5}/100$	0.0019***	0.0019***	0.0033***		
	(0.0007)	(0.0007)	(0.0010)		
$PM_{2.5}$ Level 2				0.0017*	0.0019**
				(0.0009)	(0.0009)
$PM_{2.5}$ Level 3				0.0041***	0.0041***
				(0.0012)	(0.0013)
$PM_{2.5}$ Level 4				0.0043***	0.0045***
				(0.0016)	(0.0016)
$PM_{2.5}$ Level 5				0.0026	0.0026
				(0.0018)	(0.0017)
$PM_{2.5}$ Level 6				0.0059**	0.0058**
				(0.0024)	(0.0024)
$PM_{2.5}$ Level 7				0.0070**	0.0070**
				(0.0031)	(0.0031)
Year by Month FE	YES	YES	YES	YES	YES
Community FE	YES	YES	YES	YES	YES
Weather	YES	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES	YES
Day of Week FE	NO	YES	YES	NO	YES
Holiday FE	NO	YES	YES	NO	YES
Observations	122,670	122,670	122,510	122,670	122,670
R-squared	0.335	0.335	0.335	0.335	0.335

Notes: Standard errors are two way clustered at the community-day level.
Columns 1,2,4,5 report OLS estimation; Column 3 reports IV estimation. The Kleibergen-Paap F statistic is 6.82 in Column 3.
The Cragg-Donald Wald F statistic is 1202.27 in Column 3.
$PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 3: The Impact of Air Pollution on Transaction Volume

Variables	OLS Ln(Volume)	OLS Ln(Volume)	2SLS Ln(Volume)	OLS Ln(Volume)
$PM_{2.5}/100$	0.101***	0.0948***	0.0699	
	(0.0322)	(0.0364)	(0.0684)	
$PM_{2.5}$ Level 2				0.0263
				(0.470)
$PM_{2.5}$ Level 3				0.103*
				(0.0569)
$PM_{2.5}$ Level 4				0.1070
				(0.0721)
$PM_{2.5}$ Level 5				0.1660*
				(0.0762)
$PM_{2.5}$ Level 6				0.3650***
				(0.1120)
$PM_{2.5}$ Level 7				0.4610***
				(0.1600)
Lagged $PM_{2.5}$	NO	30	NO	NO
Weather FE	YES	YES	YES	YES
Year by month FE	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	720	718	720	720
R-squared	0.766	0.770	0.768	0.768

Notes: Standard errors are in parentheses.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.
The Kleibergen-Paap F statistic for column 3 is 5.09.
The Cragg-Donald Wald F statistic for column 3 is 4.97.
$PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350.

Table 4: The Heterogeneous Impacts of Air Pollution ($PM_{2.5}$) on Transacted Prices (*per sqm*) of Local Buyers and Non-local Buyers

Variables	Non-local OLS Ln(Unit Price)	Local OLS Ln(Unit Price)	Non-local 2SLS Ln(Unit Price)	Local 2SLS Ln(Unit Price)
$PM_{2.5}/100$	0.0023***	0.0011	0.0040***	0.002
	(0.0008)	(0.0011)	(0.0012)	(0.0014)
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	YES	YES	YES	YES
Community FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	78,033	43,266	77,926	43,213
R-squared	0.356	0.306	0.356	0.306

Note: Standard errors are two way clustered at the community-day level.
Columns 1 and 2 report OLS estimation; Columns 3 and 4 report IV estimation.
The Kleibergen-Paap F statistics are 7.13 and 7.42 in these two columns, respectively.
The Cragg-Donald Wald F statistics are 760.96 and 389.83 in these two columns, respectively.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 5: Heterogeneity by Local/Non-Local on Transacted Volume

Variables	Non Local OLS Ln(Vol)	Local OLS Ln(Vol)	Non Local 2SLS Ln(Vol)	Local 2SLS Ln(Vol)
$PM_{2.5}/100$	0.1180***	0.0374	0.0647	-0.0118
	(0.0329)	(0.0273)	(0.0686)	(0.0506)
Lagged AQI	NO	NO	NO	NO
Lagged Volume	NO	NO	NO	NO
Weather FE	YES	YES	YES	YES
Year by month FE	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	720	717	718	715
R-Squared	0.763	0.802	0.765	0.802

Note: Standard errors are reported in the parentheses.
Columns 1-2 use OLS estimation; Columns 3-4 use IV estimation;
The Kleibergen-Paap F statistics are 5.09 and 5.01 in these two columns, respectively.
The Cragg-Donald Wald F statistics are 4.97 and 4.88 in these two columns, respectively.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.

Table 6: Heterogeneity by Local/Non-Local and Age (OLS)

Variables	Non Local age<33 (1) Ln(Price)	Non Local Age≥33 (2) Ln(Price)	Local Age<33 (3) Ln(Price)	Local Age≥33 (4) Ln(Price)
$PM_{2.5}$ Level 2	0.0038**	0.0027*	-0.0020	0.0014
	(0.0017)	(0.0015)	(0.0025)	(0.0018)
$PM_{2.5}$ Level 3	0.0062***	0.0041**	0.0022	0.0025
	(0.0022)	(0.0017)	(0.0030)	(0.0023)
$PM_{2.5}$ Level 4	0.0049*	0.0056**	0.0030	0.0045
	(0.00254)	(0.0027)	(0.0038)	(0.0031)
$PM_{2.5}$ Level 5	0.0025	0.0034	0.00025	0.0019
	(0.00263)	(0.0026)	(0.0041)	(0.0033)
$PM_{2.5}$ Level 6	0.0095***	0.0047	0.0037	0.00085
	(0.0032)	(0.0039)	(0.0056)	(0.0040)
$PM_{2.5}$ Level 7	0.0094**	0.0024	-0.0051	0.0089
	(0.0047)	(0.0060)	(0.0105)	(0.0070)
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	YES	YES	YES	YES
Community FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	40,234	36,473	15,666	26,397
R-squared	0.366	0.361	0.319	0.304

Note: Standard errors are two way clustered at the community-day level.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.
$PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350.

Table 7: Heterogeneity by Local/Non-Local and Home Size (OLS)

Variables	Non Local Size<75sqm (1) Ln(Price)	Non Local Size≥75sqm (2) Ln(Price)	Local Size<75sqm (3) Ln(Price)	Local Size≥75sqm (4) Ln(Price)
$PM_{2.5}$ Level 2	0.0034**	0.0030*	0.0008	0.0022
	(0.0014)	(0.0016)	(0.0020)	(0.0020)
$PM_{2.5}$ Level 3	0.0066***	0.0048***	0.0015	0.0039*
	(0.0020)	(0.0018)	(0.0028)	(0.0023)
$PM_{2.5}$ Level 4	0.0079***	0.0025	0.0049	0.0040
	(0.0025)	(0.0026)	(0.0033)	(0.0030)
$PM_{2.5}$ Level 5	0.0076***	0.0005	0.0048	-0.0008
	(0.0026)	(0.0024)	(0.0036)	(0.0031)
$PM_{2.5}$ Level 6	0.0121***	0.0034	0.0085*	-0.0032
	(0.0035)	(0.0033)	(0.0045)	(0.0038)
$PM_{2.5}$ Level 7	0.015***	-0.0002	0.0099	-0.0010
	(0.0058)	(0.0049)	(0.0087)	(0.0073)
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	YES	YES	YES	YES
Community FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	39,768	37,591	20,541	22,001
R-squared	0.364	0.382	0.304	0.357

Note: Standard errors are two way clustered at the community-day level.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.
$PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350.

Table 8: Heterogeneity by Local/Non-Local Experienced Buyers (OLS)

Variables	Non Local (1) Ln(Price)	Local (2) Ln(Price)	Non Local (3) Ln(Price)	Local (4) Ln(Price)
$PM_{2.5}/100$	0.0033*	-0.0012		
	(0.0018)	(0.0024)		
$PM_{2.5}$ Level 2			0.0014	-0.0011
			(0.0043)	(0.0048)
$PM_{2.5}$ Level 3			0.0069	0.0076
			(0.0061)	(0.0062)
$PM_{2.5}$ Level 4			0.0137**	0.0033
			(0.0057)	(0.0083)
$PM_{2.5}$ Level 5			0.0122*	0.0072
			(0.0068)	(0.0080)
$PM_{2.5}$ Level 6			0.0043	-0.0059
			(0.0061)	(0.0075)
$PM_{2.5}$ Level 7			0.0134	-0.0242*
			(0.0086)	(0.0144)
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	YES	YES	YES	YES
Community FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	17,187	10,437	17,187	10,437
R-squared	0.315	0.309	0.316	0.310

Note: Standard errors are two way clustered at the community-day level.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level.
$PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350.

Appendices

A Tables

Table A.1: The Impact of Air Pollution (AQI) on Transacted Prices (*per sqm*)

Variables	(1) Ln(Unit Price)	(2) Ln(Unit Price)	(3) Ln(Unit Price)	(4) Ln(Unit Price)
AQI/100	0.0010	0.0019	0.0019**	0.0019**
	(0.0018)	(0.0024)	(0.0007)	(0.0007)
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	NO	YES	YES	YES
Community FE	NO	NO	YES	YES
Day of Week FE	NO	NO	NO	YES
Holiday FE	NO	NO	NO	YES
Observations	122,005	122,005	121,525	121,525
R-squared	0.146	0.146	0.336	0.336

Note: Standard errors are two way clustered at the community-day level.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level

Table A.2: The Impact of Air Pollution on Transacted Prices (*per sqm*) Using Station Level Pollution Data

Variables	(1) Avg $PM_{2.5}$ Ln(Unit Price)	(2) Max $PM_{2.5}$ Ln(Unit Price)	(3) Avg AQI Ln(Unit Price)	(4) Max AQI Ln(Unit Price)
$PM_{2.5}/100$	0.0013**	0.0010**		
	(0.0007)	(0.0005)		
AQI/100			0.0014**	0.0012**
			(0.0007)	(0.0004)
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	YES	YES	YES	YES
Community FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	122,670	111,484	111,484	111,484
R-squared	0.335	0.337	0.337	0.337

Note: Standard errors are two way clustered at the community-day level.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level

Table A.3: The Impact of Air Pollution on Transacted Prices (*per sqm*)(Full Sample, Controlling for Lags)

Variables	(1) Ln(Unit Price)	(2) Ln(Unit Price)	(3) Ln(Unit Price)	(4) Ln(Unit Price)
$PM_{2.5}/100$	0.0017**	0.0016**		
	(0.0007)	(0.0007)		
AQI/100			0.0015**	0.0015*
			(0.0008)	(0.0008)
Lagged $PM_{2.5}$	10	30		
Lagged AQI			10	30
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	YES	YES	YES	YES
Community FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	122,670	122,670	120,705	119,080
R-squared	0.336	0.336	0.336	0.337

Note: Standard errors are two way clustered at the community-day level.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level

Table A.4: The Impact of Air Pollution on Transacted Prices (*per sqm*)(Local Buyers, Controlling for Lags)

Variables	(1) Ln(Unit Price)	(2) Ln(Unit Price)	(3) Ln(Unit Price)	(4) Ln(Unit Price)
$PM_{2.5}/100$	0.0015	0.0009		
	(0.0012)	(0.0011)		
AQI/100			0.0008	0.0005
			(0.0012)	(0.0012)
Lagged $PM_{2.5}$	10	30		
Lagged AQI			10	30
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	YES	YES	YES	YES
Community FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	43,266	43,266	42,595	42,024
R-squared	0.306	0.307	0.308	0.311

Note: Standard errors are two way clustered at the community-day level.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level
AQI data was only available starting in 2014.

Table A.5: The Impact of Air Pollution on Transacted Prices (*per sqm*)(Non-local Buyers, Controlling for Lags)

Variables	(1) Ln(Unit Price)	(2) Ln(Unit Price)	(3) Ln(Unit Price)	(4) Ln(Unit Price)
$PM_{2.5}/100$	0.0017**	0.0019*		
	(0.0009)	(0.0009)		
AQI/100			0.0018**	0.0020*
			(0.0009)	(0.0009)
Lagged $PM_{2.5}$	10	30		
Lagged AQI			10	30
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	YES	YES	YES	YES
Community FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	78,033	78,033	76,742	75,685
R-squared	0.356	0.357	0.356	0.357

Note: Standard errors are two way clustered at the community-day level.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level
AQI data was only available starting in 2014.

Table A.6: The Impact of Air Pollution on Transacted Prices (per *sqm*): Non-local and Local Buyers

Variables	Non-local Ln(Unit Price)	Non-local Ln(Unit Price)	Local Ln(Unit Price)	Local Ln(Unit Price)
$PM_{2.5}$ Level 2	0.0032***	0.0033***	0.0000	0.0002
	(0.0012)	(0.0012)	(0.0014)	(0.0014)
$PM_{2.5}$ Level 3	0.0057***	0.0057***	0.0021	0.0023
	(0.0015)	(0.0016)	(0.0018)	(0.0018)
$PM_{2.5}$ Level 4	0.0056***	0.0057***	0.0035	0.0038
	(0.0019)	(0.0019)	(0.0024)	(0.0024)
$PM_{2.5}$ Level 5	0.0037*	0.0037*	0.0015	0.0014
	(0.0021)	(0.0021)	(0.0026)	(0.0026)
$PM_{2.5}$ Level 6	0.0079***	0.0081***	0.0035	0.0029
	(0.0027)	(0.0026)	(0.0031)	(0.0030)
$PM_{2.5}$ Level 7	0.0079**	0.0082**	0.0035	0.0029
	(0.0039)	(0.0038)	(0.0056)	(0.0056)
Year by Month FE	YES	YES	YES	YES
House Characteristics	YES	YES	YES	YES
Weather FE	YES	YES	YES	YES
Community FE	YES	YES	YES	YES
Day of Week FE	NO	YES	NO	YES
Holiday FE	NO	YES	NO	YES
Observations	78,033	78,033	43,266	43,266
R-squared	0.356	0.356	0.306	0.306

Note: Standard errors are two way clustered at the community-day level.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level
$PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350.

Table A.7: Heterogeneity of AQI by Local/Non-Local on Transacted Volume

Variables	Non Local Ln(Vol)	Local Ln(Vol)	Non Local Ln(Vol)	Local Ln(Vol)	Non Local Ln(Vol)	Local Ln(Vol)
AQI/100	0.1130***	0.0389	0.1100***	0.0261	0.1030***	0.0263
	(0.0332)	(0.0275)	(0.0375)	(0.0315)	(0.0354)	(0.0298)
Lagged AQI	NO	NO	10	10	30	30
Lagged Volume	NO	NO	NO	NO	NO	NO
Weather FE	YES	YES	YES	YES	YES	YES
Year by month FE	YES	YES	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES	YES	YES
Observations	713	710	703	700	684	681
R-Squared	0.763	0.802	0.769	0.804	0.805	0.833

Note: Standard errors are reported in the parentheses.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level

Table A.8: The Impact of Air Pollution on Home Buyers' Sentiments (OLS)

	Baidu Index			Sofun
	(1)	(2)	(3)	(4)
Variables	Lianjia	Buy house	Soufang	Soufun Web Click
$PM_{2.5}/100$	0.0249*	0.0177**	0.0341***	0.0216**
	(0.0127)	(0.0085)	(0.0109)	(0.0086)
Lagged $PM_{2.5}$	30	30	30	30
Weather FE	YES	YES	YES	YES
Year by month FE	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	730	730	730	562
R-Squared	0.811	0.683	0.700	0.498

Note: Standard errors are reported in the parentheses.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level

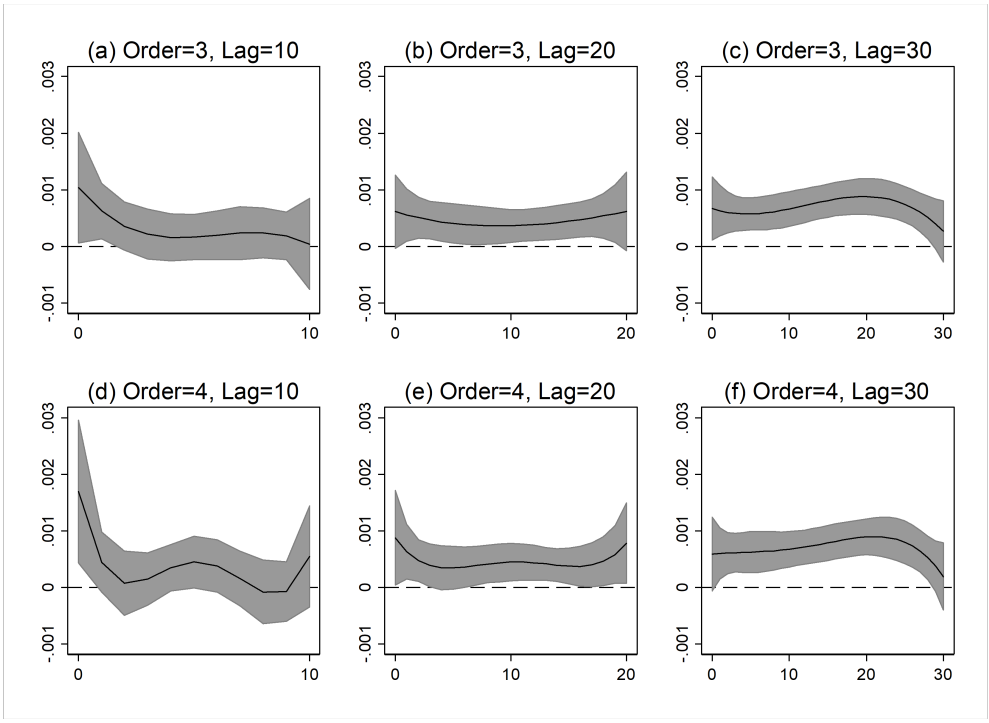
Table A.9: The Impact of Air Pollution (AQI) on Home Buyers' Sentiments

	Baidu Index			Sofun
	(1)	(2)	(3)	(4)
Variables	Lianjia	Buy house	Soufang	Soufun Web Click
AQI/100	0.019*	0.019**	0.029***	0.021**
	(0.020)	(0.009)	(0.011)	(0.008)
Lagged AQI	30	30	30	30
Weather FE	YES	YES	YES	YES
Year by month FE	YES	YES	YES	YES
Day of the week FE	YES	YES	YES	YES
Holiday FE	YES	YES	YES	YES
Observations	693	693	693	545

Note: Standard errors are reported in the parentheses.
* significant at the 0.1 level; ** significant at the 0.05 level; *** significant at the 0.01 level

B Figure

Figure B.1: The Impact of Air Pollution on Unit Price: Various Order-lag Specifications



Note: Regression coefficients with 95% confidence interval.