Journal of Environmental Economics and Management 94 (2019) 161–187

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Negotiating housing deal on a polluted day: Consequences and possible explanations☆

Yu Qin[a], Jing Wu[b,*], Jubo Yan[c]

[a] Department of Real Estate, National University of Singapore, Singapore
[b] Hang Lung Center for Real Estate and Department of Construction Management, Tsinghua University, China
[c] School of Social Sciences, Nanyang Technological University, Singapore

ARTICLE INFO

Article history:
Received 10 July 2018
Revised 14 February 2019
Accepted 17 February 2019
Available online 25 February 2019

JEL codes:
D91
Q51
Q53
R31

Keywords:
Air pollution
Housing market
Salience
Relative thinking

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 the transaction prices on a severely polluted day are 0.65% higher than those of the days without pollution, other things being equal. This translates into approximately 3.51 million *yuan* daily increase based on the average transaction volume and price on a typical day in Beijing. The heterogeneity analysis further suggests that this effect is mostly driven by non-local and low income buyers. After ruling out rational explanations, we demonstrate that our empirical results are consistent with salience theory under weak assumptions.

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 (Ito and Zhang, 2016). Alternatively, they may be more willing to migrate to cleaner cities or countries as a more expensive averting measure (Qin and Zhu, 2018). In addition to averting behaviors, air pollution may induce other behavioral changes in the context of insurance purchases (Chang et al., 2017),

☆ We are grateful to seminar participants at the National University of Singapore, Peking University, Tsinghua University, Xiamen University, Beijing Normal University, the 3rd Biennial Conference of China Development Studies, and the NUS Mini-Workshop on Air Pollution for their valuable comments. We are very grateful to Alberto Salvo and Haoming Liu for kindly sharing their data and code on thermal inversion. We appreciate the comments from Sumit Agarwal and Soo Hong Chew. We thank Keyang Li for his excellent research assistance. The editor and two anonymous reviewers lent tremendous help for us to improve the paper. Qin acknowledges funding support from the Ministry of Education - Singapore: R-297-000-129-133. Wu acknowledges National Natural Science Foundation of China (No. 71874093 and 91546113) and Tsinghua University Initiative Scientific Research Program. Yan acknowledges the funding support from Nanyang Technological University Start Up Grant: 200604393R and AcRF Tier 1 grant from Ministry of Education - Singapore: RG84/17. All errors remain ours.

* Corresponding author.
E-mail address: ireswujing@tsinghua.edu.cn (J. Wu).

https://doi.org/10.1016/j.jeem.2019.02.002
0095-0696/

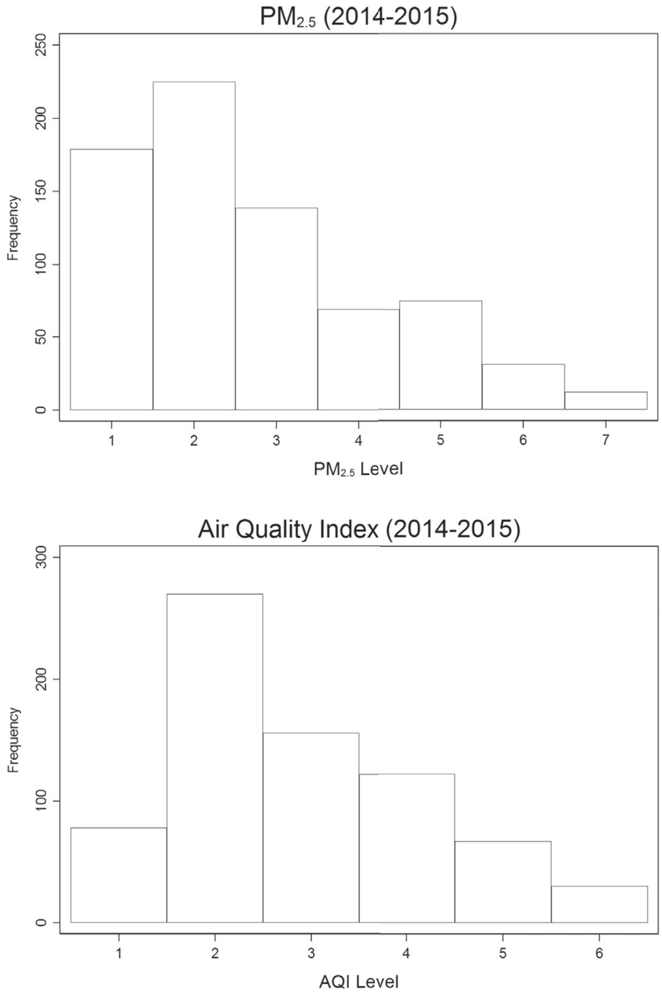

Fig. 1. Air quality in Beijing (2014–2015).
Data source: $PM_{2.5}$ data is from the U.S. Embassy in Beijing and AQI data is from Ministry of Environmental Protection (MEP).

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 an economically important 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 her mind just because of the air pollution on the contracting date. Second, as shown in Fig. 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 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.

[1] Chang et al. (2017) 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. (2017) conduct a survey in Beijing and the results show that people do not update their belief about local pollution levels based on a single-day observation.

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 100,000 transactions of resale (as opposed to new sale) 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 price context, 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 heterogeneity 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 when the buyers and sellers negotiate the price and sign the contract with the actual transaction price, we find that the transaction prices on a severely polluted day (i.e., with $PM_{2.5}$ level higher than 350) are 0.65% higher than those of the days without pollution (i.e., with $PM_{1.5}$ level lower than 35), after controlling for housing characteristics, community effects, year-by-month effects, day-of-the-week effects, weather, and holidays. Using the average transaction price and volume on a typical day, the calculated total increase in overall value of housing sold is about 3.51 million *yuan*. This effect is mainly driven by non-local buyers who are buying smaller units. Given that days with moderate pollution in Beijing are common, this is an economically significant amount. In addition to the effect on transaction price, we find that the transaction volumes do not decline and might in fact be higher on severely polluted days. Hence, selection is not an explanation of our empirical findings. We also rule out two other alternative explanations – the results are due to pollution's effect on the cognitive ability of home buyers and buyers' information update about the local pollution level.

Our evidence suggests that the positive association between air pollution and housing transaction prices is likely due to relative or salience thinking[3] of home buyers (Bordalo et al., 2012, 2013a,b) under fairly weak assumptions. Because buyers have entered the last stage of buying a house, they have determined to work and live in Beijing and moving away from the city is no longer in their choice set. Hence, buyers only choose to stay in the current residence or to purchase the house and move to a new residence which is also in Beijing. Air pollution causes a decline in living quality. In this particular context, air pollution causes the same negative shock to current living quality (i.e. current residence) and potential future living quality (i.e. residence planning to purchase). However, although the absolute difference between potential future living quality and current living quality stays unchanged, the *proportional* improvement in living quality over the current one actually increases on polluted days. Assuming that living quality can be quantified with numbers, this intuition can be shown with a simple numerical example. If the current living quality is 100 and the new house provides a living quality of 150, the absolute increase in living quality is 50 and the proportional increase is 50/100 = 50%. With air pollution negatively influencing living qualities (e.g. −20), the absolute difference is still 50 but the proportional increase is now 50/(100-20) = 62.5%. Due to relative thinking, buyers tend to think a 62.5% increase being more attractive than a 50% increase and thus are willing to pay a higher price for this improvement.

In the language of salience theory, when considering different living alternatives, the buyer's attention is drawn more to living quality by its larger relative change due to pollution; thus, price becomes less salient. Consequently, on a polluted day, buyers would be more likely to 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 those buyers currently having lower living qualities. Consistently, we find no effect of air pollution on transaction prices of local buyers who likely already owned a house in Beijing prior to the transaction or living together with their families. In addition, the effect pertains to those non-local buyers and who are buying smaller units. As supplementary evidence, we find that Baidu's (a search engine in China similar to Google) searches for home-purchase related key words significantly increase 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 of this evidence collected from different sources indicates that people tend to value housing more on polluted days due to the salience of living quality improvement.

Our paper makes two major contributions. First, we provide the first evidence consistent with salience theory in the housing market. Decisions made by housing market participants are substantial for their lifetime well-being. Thus, behavioral biases are likely to lead to unfavorable outcomes. Busse et al. (2015); Conlin et al. (2007), among others, assert the importance of testing for behavioral 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 in a bilateral negotiation setting. All empirical studies (e.g. Busse et al. (2015)) that we are aware of have relied on the volume of transactions or propensity of purchasing to demonstrate behavioral biases such as projection bias or salience. We differentiate ourselves by examining both transaction price (thus inferring willingness to pay) and volumes in our empirical analysis.

[3] In the economics literature, salience theory refers to the decision theory that was developed by (Bordalo et al., 2012, 2013a,b). It shares a similar intuition with relative thinking theory. In the current paper, we argue that they both explain our empirical findings. Because they share a similar intuition, we use the two terms interchangeably when we discuss the intuition. When we give examples of respective theories, we will discuss them separately.

Second, 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) 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. (2016) 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; Qin and Zhu, 2018; Sun et al., 2017; Viard and Fu, 2015; Zhang and Mu, 2017; Zhang et al., 2017).

The remainder of the paper is organized as follows. Section 2 introduces the background information 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 estimation; 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 households in Beijing live in self-owned houses, while the rest of 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.[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 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 (Fig. 2 panel A). To curb speculative activities in the housing market, Beijing's government implemented 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] Eligible home buyers in Beijing can either buy new houses from the developers or resale houses from home owners. Housing resale 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 housing resale transactions.

Fig. 3 introduces the typical procedures for housing resale transactions in Beijing. First, a potential buyer contacts one or more real estate agents and communicates her 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, 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.

[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.

[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.

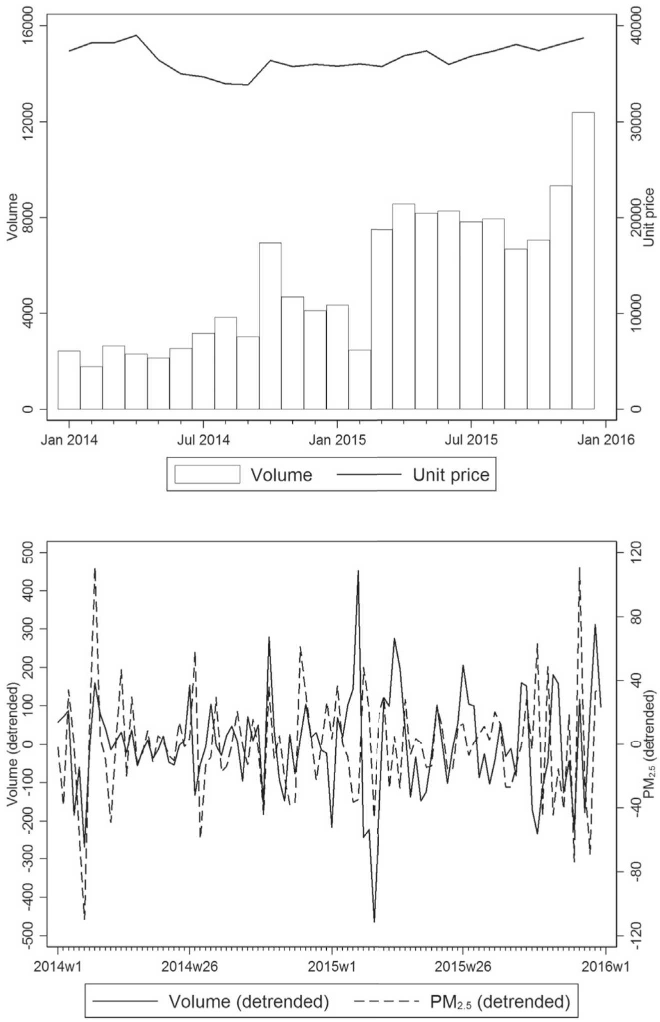

Fig. 2. Housing prices, transaction volume, and pollution in Beijing (2014–2015).
Data source: $PM_{2.5}$ data is from the U.S. Embassy in Beijing. Price and volume are calculated from the data provided by the housing brokerage firm.

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. However, a potential concern about the official AQI data is that the local government may manipulate it. As a pollution abatement effort, the air quality

[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/news25941.html for the new ambient air quality standards (GB3095-2012).

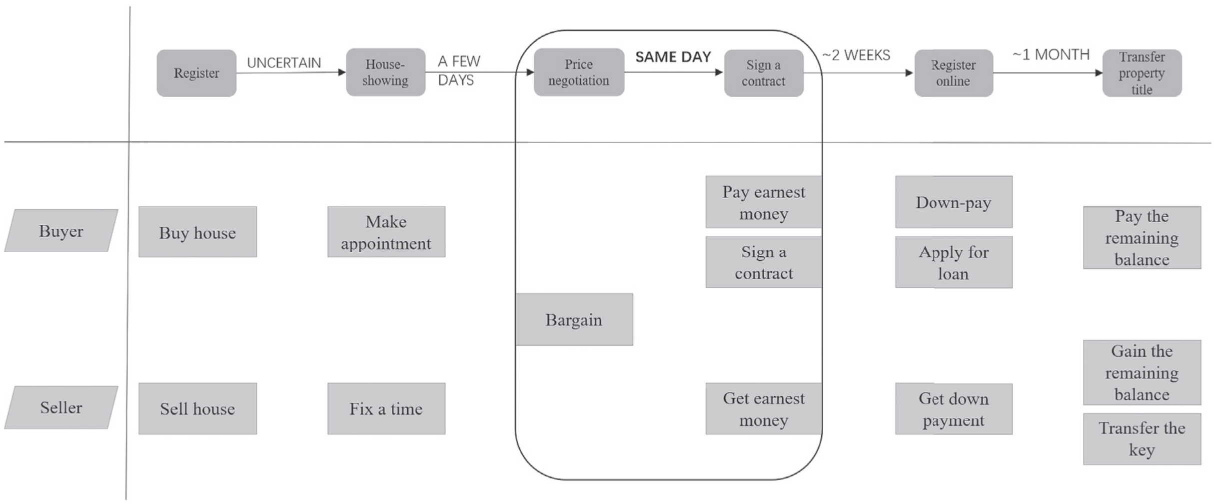

Fig. 3. Transaction process of housing resales in Beijing. *Note:* Information collected by the authors from the housing brokerage firm.

of a city is now associated 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) 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]

Fig. 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. Given the key role of variation in air pollution level, we also plot the daily detrended $PM_{2.5}$ level and transaction volume in Fig. 2 panel B. The pattern further confirms that the $PM_{2.5}$ level changes provide sufficient variation to examine the effect of severe air pollution on housing transactions.

3.2. Housing transaction data

Transaction data for existing home sales is provided by one of the largest housing brokerage firms in Beijing. The sample covers all transactions of resale housing units with the assistance of this brokerage firm 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.[12] As mentioned in the previous section, a critical feature of the housing transactions in the resale market 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 2.96 million *yuan*. The average price per square meter is 36,882 *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.

[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.

[12] We are required not to release the name of brokerage firm. Its market share in Beijing's housing resale market was around 40–45% during our sample period, and thus it is reasonable to expect that our dataset can well represent the housing resale market in Beijing. Unfortunately, we cannot access similar data beyond 2014 and 2015.

Table 1
Summary statistics.

Sample period: 2014.01.01–2015.12.31; 5515 communities						
Variable	Explanation	Observations	Mean	Std. Dev.	Min	Max
pm	$PM_{2.5}$	130,342	92.2894	82.2383	5.2	537.25
transactionprice	Transaction price (*yuan*)	130,342	2,958,713	1,685,498	111200	43,700,000
sqmprice	Unit price (*yuan*)	130,342	36881.94	14350.32	5221.66	149275.4
vol	Transaction volume (unit)	720	181.0306	134.3656	1	863
bedroom	Number of bedrooms	130,334	2.00887	0.73445	1	4
area	Area (*sqm*)	130,342	82.3063	34.28138	10	504
currentfloor	Floor	130,342	7.2260	5.7259	1	40
green_lvl	Green rate	113,861	0.3316	0.0695	0.04	0.9
center	Distance to CBD (meters)	118,191	13325.67	7837.344	882	70147
face1	North-south exposure	130,342	0.4783	0.4995	0	1
face2	Facing south	130,342	0.2557	0.4363	0	1
face3	Other facing	130,342	0.2660	0.4419	0	1
type_buil g1	Slab type apartment	130,342	0.2499	0.4329	0	1
type_buil g2	Tower block	130,342	0.1789	0.3833	0	1
type_buil g3	Combined type	130,342	0.5713	0.4949	0	1
type_house1	Apartment	130,342	0.0199	0.1396	0	1
type_house2	Ordinary residence	130,342	0.9801	0.1396	0	1
only_	Only residence	124,518	0.7047	0.4562	0	1
full_	Resold within 5 years	109,558	0.9112	0.2844	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.

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. In particular, with the housing purchase restriction, all the housing market participants in our sample should have lived in Beijing for at least several years, and thus they should not change their belief about the air quality in Beijing based on just 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 behavioral literature (Busse et al., 2015; Chang et al., 2017; Conlin et al., 2007), very short-term exogenous shocks such as air pollution and weather can change people's decisions and behaviors due to different reasons. Although the decision of purchasing a house is more substantial than buying a consumer good such as winter clothes or even cars, 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/or sellers' willingness to accept (WTA), hence changes the market outcome.

The housing resale 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. Fig. 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.

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

Fig. 4. Inferred WTP and WTA changes using market outcomes. *Notes:* WTP is short for Willingness To Pay; WTA is short for Willingness To Accept. Price and volume refer to the market transaction price and volume. Arrows pointing up and down indicate the direction of change. Arrows pointing both directions indicate that the direction of change is unclear. The dashes indicate no change.

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 housing attributes, community fixed effects, year-by-month fixed effects, weather controls, a dummy variable for national holidays, and day-of-the-week fixed effects. 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:

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

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.[13] $Weather_t$ controls for weather on day t, including temperature, wind speed, dew point, and dummy variables for fog, snow, rain, and thunder.[14] $Hedonic_j$ includes all the characteristics of housing unit j. In the full specification, the community fixed effects, year-by-month fixed effects, dummy variable for national holidays, and day-of-the-week fixed effects have been controlled for additionally. We adopt the robust standard error two-way clustering at the community-day level.

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 allow 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 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 is an exogenous shock in the very short term, to address possible concerns over endogeneity problems, we also conduct IV estimations for our main results. We use thermal inversion to instrument for air pollution, which can be endogenous to local economic activities. 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 obtain the NOAA atmospheric data.[15] 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 temperature readings at different layers to construct the thermal inversion data.[16]

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

Hence, in the first stage of the IV regression, we include 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 include the following: the squared and cubed temperature differences, wind speed, and

[13] We follow studies of Chinese housing market to use unit price in our analyses. Using total price as the main dependent variable does not change our results and we have included a table in the appendix that replicates our main results to show this. See Table B.13 for details.

[14] 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.

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

[16] 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.

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)
$PM_{2.5}/100$	0.0018***	0.0018***	0.0032***		
	(0.0007)	(0.0007)	(0.0009)		
$PM_{2.5}$ Level 2				0.0014	0.0015*
				(0.0009)	(0.0009)
$PM_{2.5}$ Level 3				0.0032***	0.0033***
				(0.0012)	(0.0012)
$PM_{2.5}$ Level 4				0.0039**	0.0040**
				(0.0016)	(0.0016)
$PM_{2.5}$ Level 5				0.0021	0.0021
				(0.0017)	(0.0017)
$PM_{2.5}$ Level 6				0.0054**	0.0054**
				(0.0023)	(0.0023)
$PM_{2.5}$ Level 7				0.0065**	0.0065**
				(0.0031)	(0.0030)
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	108,514	108,514	108,358	108,514	108,514
R-squared	0.334	0.334	0.334	0.334	0.334

Notes: Robust 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 6.89 in Column 3. The Cragg-Donald Wald F statistic is 966.82 in Column 3. Threshold values for maximal IV relative bias of 5%: 21.12; 10%: 10.91; 20%: 5.69. Note that these threshold values only apply to the non clustered standard errors cases. $PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350. * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

their lagged terms.[17]

5. Main findings

Table 2 shows the impact of air pollution on the day of the negotiation on the transaction prices (per square meter, or *sqm* for short). 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 significant at the 1% level. Specifically, an increase of $PM_{2.5}$ by 100 on the day of the negotiation leads to an approximately 0.18% increase in the per *sqm* transaction price. Column 3 reports the two-stage least square estimation where we use thermal inversion, wind speed, and wind direction to instrument for daily $PM_{2.5}$.[18] The coefficient estimate using 2SLS is slightly larger compared to 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 standard 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 during the sample period, it translates into approximately 5,500 *yuan* or USD 847 (i.e., based on the exchange rate on December 2015), which is 12% of the annual per capita disposable income in Beijing in 2015 (48,458 *yuan*). Using average transaction price (2,958,713 *yuan*) and volume (181.03) on a typical day, the calculated total increase is approximately 1.11 million *yuan* per day for the

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

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

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. The detailed first stage regression results are provided in Table B.1 in the appendix. The data we used in our IV analysis is the same as the one used by Liu and Salvo (2018). We thank the authors for sharing their data.

[18] The first stage regression results can be found in Table B.1 in the appendix.

whole city, which is an economically significant amount.

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 10% level or higher. 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 0.65% 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 19,390 *yuan* (USD 2,985) per housing unit or approximately 3.51 million *yuan* for the whole city on a typical day.[19] In summary, the result indicates that air pollution on the negotiation day increases the transaction price.

We conduct a set of 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 government and this might lead to biased estimates (Chen et al., 2012). The result is reported in Table B.2 and very similar to the ones using $PM_{2.5}$. Second, 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 B.3). Third, we adopt a polynomial distributed lag model, which can mitigate the concern of multicollinearity across the lag terms of air pollution (Almon, 1965).[20] The results are presented in Fig. C.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 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 when the house was shown.

Fourth, we explore the spatial variation in pollution level, because there are more than 20 monitoring stations in the city. Although we do not have the information on the exact location of the negotiation sites, we take the location of the property as an approximation.[21] The regression results are shown in Table B.4 in the appendix. With the full set of control variables, the average $PM_{2.5}$ is not significant at the conventional level but with a positive coefficient. The maximum level of $PM_{2.5}$ is significant at 10 percent level.

Fifth, we try to control for some additional variables in our main regression including major policy changes in the housing market over our sampling period and a dummy variable that represents buyers who are paying cash. In addition we control for the $PM_{2.5}$ level on the buyer's registration date as a proxy of the air quality on the housing viewing date.[22] We find that the inclusion of such variables does not change the main results. Table B.5 shows the results with column 4 controlling for all the mentioned variables.

Lastly, we supplement our Beijing sample with a subsample of transactions in the other two major cities in China–Shanghai and Guangzhou–for the same period. Table B.6 in the appendix shows the results. Our results are robust to the inclusion of Shanghai and Guangzhou data. The estimated coefficients of the AQI level even become larger. Because the housing markets in Shanghai and Guangzhou are less concentrated in terms of the brokerage firms' market share when compared with Beijing and we do not have access to the majority of resale transactions, we only include this result as a robustness check.

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 $PM_{2.5}$,

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

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

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

[19] Calculated as $2,958,713 yuan \times 181.0306 units \times (e^{0.0065} - 1)/1,000,000$.

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

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

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.

[21] The contract is usually signed in one of the brokerage firm's outlet and usually the nearest one to the transacted property but it is also possible that the seller and buyer sign the contract at a different location. We thank an anonymous reviewer for pointing out that we can explore the spatial variation in terms of air pollution level.

[22] We thank a reviewer for pointing out the fact that these factors could affect the final transaction price especially the $PM_{2.5}$ on the viewing date. Unfortunately, our dataset does not record such information so we cannot control for the pollution on the viewing date directly. However, because a large portion of the buyers get registered on the day they view the housing units, we use the air pollution level on the registration day as a proxy.

Table 3
The impact of air pollution on transaction volume.

Variables	OLS Ln (Volume)	OLS Ln (Volume)	2SLS Ln (Volume)	OLS Ln (Volume)
$PM_{2.5}/100$	0.0995*** (0.0399)	0.0973*** (0.0459)	0.0620 (0.0669)	
$PM_{2.5}$ Level 2				0.0121 (0.0461)
$PM_{2.5}$ Level 3				0.0832 (0.0557)
$PM_{2.5}$ Level 4				0.0901 (0.0707)
$PM_{2.5}$ Level 5				0.1668** (0.0747)
$PM_{2.5}$ Level 6				0.3414*** (0.110)
$PM_{2.5}$ Level 7				0.4625*** (0.157)
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	720	718	720
R-squared	0.742	0.745	0.744	0.744

Notes: Robust standard errors are in parentheses.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
The Kleibergen-Paap F statistic for column 3 is 5.09. The Cragg-Donald Wald F statistic for column 3 is 4.97.
Threshold values for maximal IV relative bias of 5%: 21.12; 10%: 10.91; 20%: 5.69. Note that these threshold values only apply to the non clustered standard errors cases.
$PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350.

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 buyers' WTP is significantly higher on more polluted days, based on the nine possible outcomes in Fig. 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 relative thinking and salience theory.

6. Rational explanations

In the previous section, we have shown that the transaction prices are significantly higher, and volumes do not decrease (and may in fact increase) 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. To further rule out selection on transacted housing units, we conduct a balancing test with major housing attributes. The results are shown in Table B.7. It is easy to notice that none of the t-test is significant at 10% level. This balancing test results help us to rule out the possibility that transacted housing units are different on polluted days.

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-localOLS Ln (Unit Price)	LocalOLS Ln (Unit Price)	Non-local2SLS Ln (Unit Price)	Local2SLS Ln (Unit Price)
$PM_{2.5}/100$	0.0022***	0.0013	0.0038***	0.0018
	(0.0008)	(0.0011)	(0.0011)	(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	69,061	37,962	68,956	37,911
R-squared	0.357	0.302	0.357	0.301

Note: Robust 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 7.21 and 7.48 in these two columns, respectively.
The Cragg-Donald Wald F statistics are 612.76 and 311.32 in these two columns, respectively.
Threshold values for maximal IV relative bias of 5%: 21.12; 10%: 10.91; 20%: 5.69. Note that these threshold values only apply to the non clustered standard errors cases.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Explanation two: information update

A second explanation that may seem straightforward is information update. That is, market participants learn more about local pollution from the pollution level on the transaction date. This should not be an explanation of our empirical finding. As discussed in the background part of the current paper, severe air pollution is not a rare event in Beijing. In fact, as shown in Fig. 1, 118 days of the two-year sampling period had a $PM_{2.5}$ level higher than 150. With the AQI measure, it is similar that more than 90 days were considered to be heavily polluted out of the two-year sampling period. More importantly, to become an eligible housing buyer in Beijing, one needs to have a Beijing *hukou* (i.e. local residents who grow up in Beijing) or needs to live and work in Beijing for at least five consecutive years. This ensures that all the market participants have sufficient exposure to local pollution and should not update their beliefs just over a one day heavy pollution.

Explanation three: cognitive function changes induced by pollution

Another explanation is that the air pollution affects individuals' cognitive abilities, which then affect 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 buyers and sellers by impairing their cognitive abilities or lowering their productivity during the negotiation, rational theories would suggest price or volume change in the transactions.

Our heterogeneity analysis helps 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,[23] 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.[24] Fig. 5 (summarized from the estimation results in Table B.10, 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, Fig. 6 (summarized from the estimation results in Table B.10, 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 10% level for non-local buyers (most coefficients are significant at 1% level). The heterogeneous impact of air pollution in transaction volumes is shown in Table 5. The OLS results indicate that more non-local buyers purchase housing units on polluted days, whereas the number of purchased houses are not affected by air pollution in the local buyer group.[25]

One may further argue 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

[23] The first two digits represent the birth province of a Chinese citizen.
[24] The results are very similar if lagged pollution measures have been controlled for (Tables B.8 and B.9).
[25] The results are also similar if we use the AQI as the main regressor (Table B.11). None of the coefficients are significant in the IV estimations. However, the estimated coefficients have different signs for local and non-local buyers.

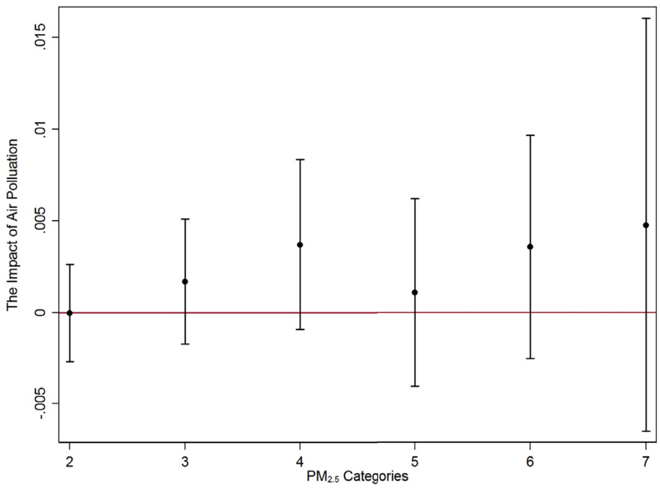

Fig. 5. The impact of air pollution on unit price (local buyers). *Note:* Regression coefficients with 95% confidence interval are reported in the graph. The baseline category is $PM_{2:5}$ Level 1.

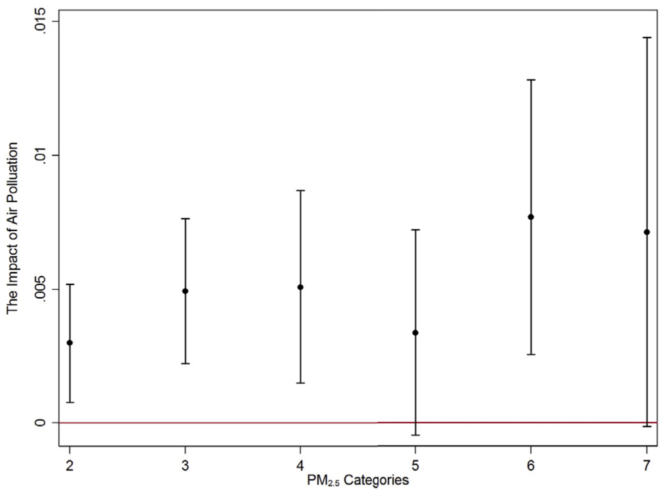

Fig. 6. The impact of air pollution on unit price (non-local buyers). *Note:* Regression coefficients with 95% confidence interval are reported in the graph. The baseline category is $PM_{2:5}$ Level 1.

receive their college degrees from one of the city's 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 how relative thinking and salience theory can explain our empirical results. Relative thinking is an intuitive explanation of many existing empirical findings, from both laboratory experiments and field data. It argues that people sometimes evaluate alternatives based on relative changes instead of absolute changes. Azar (2007) and Bushong et al. (2015) discuss relative thinking theory in details.[26] Salience theory is built on relative thinking theory and shares a similar intuition but provides more theoretical foundation. It argues that, when comparing alternatives, decision makers pay more attention to a certain attribute because the attribute is more distinct in relative term across different alternatives. Hence, the attribute 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; Hastings and Shapiro, 2013).

[26] A simple example they discussed is that an early morning flight departing at 6am that costs $100 and consumers would be unwilling to pay $30 more to switch to a later flight departing at 9am. However, if the early flight costs $300, consumers would be willing to pay more than $30 to switch to the later flight.

Table 5
Heterogeneity by local/non-local on transacted volume.

Variables	Non-LocalOLS Ln (Vol)	LocalOLS Ln (Vol)	Non-Local2SLS Ln (Vol)	Local2SLS Ln (Vol)
$PM_{2.5}/100$	0.1168***	0.0359	0.0577	−0.0215
	(0.0407)	(0.0315)	(0.0670)	(0.0488)
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	0.742	0.776	0.743	0.775

Note: Robust 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.
Threshold values for maximal IV relative bias of 5%: 21.12; 10%: 10.91; 20%: 5.69. Note that these threshold values only apply to the non clustered standard errors cases.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

For relative thinking and salience theory to be valid explanations, it is important to recognize the market participants' choice sets. It is reasonable to argue that *people who enter the last stage of buying a house are determined 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 consistent with the mental accounting and narrow bracketing literature (Kahneman, 2003; Read et al., 1999; Thaler, 1999). It is also worth noting that the choice set or choice context is important in previous studies as well. For example, Busse et al. (2015) discuss the effects of weather on the purchase of convertible cars. Thus, they implicitly assumed that the only alternatives in the choice set are non-convertible cars, and not buying a car is not a relevant alternative.

We now illustrate the relative thinking and salience theory in our context through a simple example.[27] For simplicity, we assume that people care about the quality (q) and price (p) of their living conditions. If a buyer is purchasing a house–either as a first time buyer or to upgrade her living quality–she would consider whether the living quality improvement over her current residence is worth the money that she is paying for the housing unit. The living quality improvement can be denoted as $q_{new} - q_{current}$ and the asking price of the new housing unit is p_{new}. Air pollution, being a negative shock, would reduce her living quality in both her current residence and the potential new residence. Assuming that the negative shock caused by air pollution, Δ, is positive, the living quality improvement is still $(q_{new} - \Delta) - (q_{current} - \Delta) = q_{new} - q_{current}$ under absolute thinking, same as on a clear day. Therefore, she should not change her mind on how much she would pay for the improvement or the new housing unit.

However, as predicated by relative thinking theory, the buyer would be willing to pay a higher amount for the same housing unit if she is a relative thinking decision maker. Because the *relative* living quality improvement under pollution is $\frac{(q_{new}-\Delta)-(q_{current}-\Delta)}{q_{current}-\Delta} = \frac{q_{new}-q_{current}}{q_{current}-\Delta} > \frac{q_{new}-q_{current}}{q_{current}}$, the air pollution or negative shock increases the willingness to pay for the living condition improvement and she is now willing to accept a higher p_{new}. This is the same intuition as discussed in Lian et al. (2017) where they use a controlled experiment to show that return rate improvement in investment is more salient when the starting return rate is lower.

With salience theory, the intuition is that decision maker's attention is drawn to the attribute that has a bigger relative change. This is achieved by introducing a salience function that is increasing in the relative change. With air pollution, the relative change in living quality is bigger so people pay more attention to the quality attribute of the new housing units relatively to the price attribute. To show a numerical example, assume that the decision maker's utility function is $u = \sigma_q q - \sigma_p p$, where q is living quality and p is the price of the corresponding living quality. σ_q and σ_p are respective weights that the decision maker put on quality and price. Without pollution, the utility increase obtained from moving to the new residence is $\sigma_q(q_{new} - q_{current}) - \sigma_p(p_{new} - p_{current})$. With pollution, it is $\sigma_{q\cdot polluted}(q_{new\cdot polluted} - q_{current\cdot polluted}) - \sigma_p(p_{new} - p_{current})$. Observing that $q_{new\cdot polluted} - q_{current\cdot polluted} = q_{new} - \Delta - (q_{current} - \Delta) = q_{new} - q_{current}$ and $\sigma_{q\cdot polluted} > \sigma_q$, the utility gain from moving to the new residence is larger on polluted days if the only change is air quality. Hence, buyers would be now willing to accept $p_{new\cdot polluted} > p_{new}$.[28] The appendix provides a formal analysis of this idea by adopting the formulation by

[27] We also adopt the formulation in Bordalo et al. (2013b) and provide a more thorough analysis in the appendix.

[28] Some may worry that moving into the new residence not only improves the living quality in terms of the indoor environment but also other aspects such as meeting school quality needs. It is worth noting that our extensive use of the fixed effects in our main analysis, especially the community-level fixed effects, should have taken care of such concerns. Some may further argue that the shock caused by air pollution is heterogeneous on different housing units, we think this would not affect our explanation because it is highly unlikely that the magnitude of shock is correlated with whether the agent is moving in or moving out of the housing unit. That is, in our sample, there are people moving out of the units that are less affected and moving into the more affected units (e.g. the latter one is an old house with school district). At the same time, there should also be people moving out the units that are more affected and moving into the less affected units (e.g. one's child has graduated and the family is moving to a house without school district but better quality). This is plausible because we are examining the resale market in which the supply was largely fixed for our sampling period.

Table 6
The Heterogeneous Impacts of Air Pollution ($PM_{2.5}$) on Transacted Prices (*per sqm*) of Units of Different Sizes (*sqm*).

Variables	Size $\leq$ 58.1(1) Ln (Unit Price)	58.1 $<$ Size $\leq$ 74(2) Ln (Unit Price)	74 $<$ Size $\leq$ 97.6(3) Ln (Unit Price)	Size $>$ 97.6(4) Ln (Unit Price)
$PM_{2.5}/100$	0.0033**	0.0031***	−0.0001	0.0012
	(0.0013)	(0.0011)	(0.0011)	(0.0010)
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	25,849	27,119	25,945	27,516
R-squared	0.329	0.368	0.329	0.356

Note: Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Bordalo et al. (2013b).

Based on the discussion so far, the salience explanation generates prediction that is consistent with our empirical result as well as some additional predictions:

1. Air pollution decreases living quality and draws attention to the quality attribute (relative to price). Therefore, buyers would be willing to accept higher prices.
2. The worse the buyer's current living condition is, the more she is affected by the salience thinking because the change in relative improvement is larger after hit by air pollution and hence larger increase in σ_q.
3. Air pollution draws attention to living quality; thus, more people would be thinking about improving their living conditions.

Our main result is consistent with prediction 1. In particular, we observe an increased transaction price and non-decreasing volume that indicate an increase in buyers' WTP. For prediction 2, we do not directly observe the buyers' current and potential future living qualities but we can try to approximate it in several dimensions. Firstly, local people generally have better current living quality than non-local people because they either already have a house in Beijing or they share a house with their families. For non-local people, most of them have to rent especially when they are young, and the living quality in a rental unit is usually worse than one's own house. Table 4 provides evidence that is consistent with this statement. If we divide all transactions in our sample into two groups with local and non-local buyers, we find that the effect is only significant for non-local buyers though the estimated coefficients are positive in both groups. Secondly, those who are buying bigger units tend to be wealthier and currently enjoying better living qualities. In Table 6, we divide our sample equally into four categories using the size of the transacted units. The table shows that those who are purchasing bigger units (greater than median and likely to have a better current living quality) are not significantly affected by the pollution level on the contracting date, while those buying smaller units (smaller than median and likely to have a worse current living quality) are significantly affected by the pollution. Table 7 combines these two factors and the result is very similar.

The results from the heterogeneous analyses also suggest that those who are at disadvantage (i.e. non-local buyers and buyers purchasing smaller units) are mostly affected by the air pollution. Because these people tend to be new immigrants to the city whose income are low, the impact of air pollution on this group of buyers may significantly worsen their situation. This further justifies that the environmental policies aiming to reduce air pollution will also help to alleviate disparity between different social groups.

For prediction 3, we analyze the sentiment data (i.e. search engine and website visits) to provide some evidence. Specifically, to test prediction 3, 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 housing resale 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:

$$Index_t = Constant + \beta PM_{2.5_{n,t}} + \lambda Weather_t + Month_t + Holiday_t + DOW_t + \epsilon_t, \tag{6}$$

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 effects, day-of-the-week fixed effects, and holiday fixed effects. 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 8 (and Table B.12, for a robustness check using the AQI as the main regressor), people search for these housing-related keywords more on polluted days. They also visit the broker's website more.[29] These results support our argu-

[29] 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."

Table 7
Heterogeneity by local/non-local and home size (OLS).

Variables	Non-Local Size $<$ 74*sqm* (1)Ln (Price)	Non-Local Size ≥74*sqm* (2)Ln (Price)	Local Size $<$ 74*sqm* (3)Ln (Price)	Local Size ≥74*sqm* (4)Ln (Price)
$PM_{2.5}$ Level 2	0.0030**	0.0027*	0.0002	0.0020
	(0.0014)	(0.0015)	(0.0021)	(0.0019)
$PM_{2.5}$ Level 3	0.0060***	0.0041**	0.0004	0.0036
	(0.0018)	(0.0017)	(0.0027)	(0.0022)
$PM_{2.5}$ Level 4	0.0065***	0.0026	0.0045	0.0038
	(0.0023)	(0.0026)	(0.0032)	(0.0029)
$PM_{2.5}$ Level 5	0.0064***	0.0007	0.0036	−0.0007
	(0.0025)	(0.0023)	(0.0036)	(0.0032)
$PM_{2.5}$ Level 6	0.0108***	0.0037	0.0085*	−0.0030
	(0.0035)	(0.0032)	(0.0046)	(0.0037)
$PM_{2.5}$ Level 7	0.0133**	−0.0008	0.0109	0.0006
	(0.0055)	(0.0050)	(0.0093)	(0.0067)
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	35,458	32,824	17,967	19,158
R-squared	0.365	0.385	0.297	0.351

Note: Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. $PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350.

Table 8
The impact of air pollution on home buyers' sentiments (OLS).

Variables	Baidu Index			Sofun
	(1) Lianjia	(2) Buy house	(3) Soufang	(4) Soufun Web Click
$PM_{2.5}$/100	0.0239*	0.0177**	0.0341***	0.0216***
	(0.0132)	(0.0088)	(0.0112)	(0.0076)
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: Robust standard errors are reported in the parentheses.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

ment that pollution reminds people 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.

8. Conclusion

In this paper, we document the immediate effect of air pollution on housing market transactions and also provide a plausible explanation–salience thinking in the housing market. We find that the per unit transaction price in Beijing's housing resale market on a severely polluted day is 0.65% higher than that of the days without pollution, controlling for other factors. One possible explanation is that, on polluted days, people care more about improving their living quality by moving to a new residence because the relative improvement of living quality is larger. Thus, pollution induces salience thinking and buyers put more weight on quality of the housing. As predicted by the salience theory, this effect is more prominent for those who have worse current living conditions. Accordingly, we find that non-local home buyers and/or those buying small houses, are mostly subject to such salience thinking.

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. (2017), who have 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). If air pollution can potentially change behaviors in an important market such as housing market, 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.

The finding in this paper also has important implications in environmental policy evaluation. While effective policies to reduce air pollution are preferable, environmental policies educating individuals to mitigate their exposure to air pollution's adverse effects are equally important. For instance, from the perspective of reducing the morbidity and mortality consequences of air pollution, people have been well advised to stay indoor under severe air pollution. However, from the perspective of reducing the behavioral bias caused by air pollution, policy makers may need to provide more information to the public on how air pollution could influence decision making. This will help to raise the public awareness on the behavioral consequence of air pollution.

Appendices

A. Prediction under Salience Theory

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:

$$\sigma(a_k, \overline{a}) = \frac{|a_k - \overline{a}|}{a_k + \overline{a}} \tag{A.1}$$

where a_k represents the attribute of good k and $\overline{a}$ 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). More importantly, as moving out of the city in the very short run is *not* an option, there are two options left in the buys' choice set – purchasing the house or continuing to rent.

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

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 buyers' 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})[30]. 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 $p_{buy} > p_{rent}$.[31] The reference good is thus $(\overline{q}, \overline{p})$ where $\overline{q} = \frac{q_{buy}+q_{rent}}{2}$ and $\overline{p} = \frac{p_{buy}+p_{rent}}{2}$. 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},[32] reducing the quality of living for housing owners and renters. Using the salience function in Equation (A.1), it is easy to show that air pollution increases the salience of living quality relative to price.[33] 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 both buying and renting; thus, the living quality between buying and renting becomes proportionally larger though 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 on (i) prices and (ii) the quality ranking of the two goods.”

[30] 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.

[31] 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.

[32] 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 $\Delta_{buy} < \Delta_{rent}$.

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

B. Tables

Table B.1
First Stage Results for IV Estimates.

VARIABLES	pm	pm	pm	pm	pm	pm
wspdGround	−0.216	−0.221	−0.207	−0.259	−0.259	−0.257
	(0.206)	(0.200)	(0.203)	(0.230)	(0.230)	(0.231)
dtp1000_G	−0.00845	−0.0156	0.00477	0.00401	0.00401	0.00177
	(0.0364)	(0.0357)	(0.0352)	(0.0371)	(0.0371)	(0.0372)
dtp925_1000	0.151***	0.154***	0.149***	0.105***	0.105***	0.103***
	(0.0368)	(0.0361)	(0.0358)	(0.0336)	(0.0336)	(0.0335)
dtp850_925	0.0326	0.0351	0.0270	0.0719*	0.0719*	0.0740*
	(0.0472)	(0.0477)	(0.0432)	(0.0422)	(0.0422)	(0.0423)
dtp700_850	−0.0968***	−0.0977***	−0.0961***	−0.108***	−0.108***	−0.102***
	(0.0330)	(0.0330)	(0.0310)	(0.0343)	(0.0343)	(0.0349)
dtp500_700	0.255	0.260	0.237	0.137	0.137	0.121
	(0.216)	(0.210)	(0.208)	(0.188)	(0.188)	(0.185)
north	0.0671	0.0882	0.0403	−0.0708	−0.0708	−0.0580
	(0.221)	(0.224)	(0.202)	(0.187)	(0.187)	(0.188)
east	0.167	0.188	0.138	0.0730	0.0730	0.0840
	(0.213)	(0.216)	(0.193)	(0.178)	(0.178)	(0.179)
south	0.0536	0.0716	0.0275	−0.0228	−0.0228	−0.00814
	(0.223)	(0.226)	(0.202)	(0.180)	(0.180)	(0.181)
west	0.121	0.152	0.0680	−0.0484	−0.0484	−0.0333
	(0.232)	(0.234)	(0.214)	(0.194)	(0.194)	(0.195)
wspdlow_dtp1000 _Gpos	0.0362	0.0479	0.0202	0.0863	0.0863	0.0730
	(0.0898)	(0.0885)	(0.0861)	(0.0889)	(0.0889)	(0.0891)
wspdlow_dtp925 _1000pos	−0.267	−0.316	−0.186	0.0871	0.0871	0.0882
	(0.211)	(0.206)	(0.206)	(0.191)	(0.191)	(0.191)
wspdlow_dtp850 _925pos	−0.209	−0.221	−0.176	−0.102	−0.102	−0.104
	(0.300)	(0.302)	(0.274)	(0.276)	(0.276)	(0.277)
wspdlow	0.0886	0.0849	0.0925	−0.0537	−0.0537	−0.0369
	(0.103)	(0.101)	(0.0984)	(0.0966)	(0.0966)	(0.0970)
dtp1000_Gpos	−0.00231	0.00191	−0.0102	0.00664	0.00664	0.00996
	(0.0478)	(0.0472)	(0.0459)	(0.0479)	(0.0479)	(0.0479)
dtp925_1000pos	−0.0728	−0.0661	−0.0929	−0.0959	−0.0959	−0.0911
	(0.150)	(0.145)	(0.149)	(0.141)	(0.141)	(0.141)
dtp850_925pos	−0.00976	−0.0111	−0.0152	−0.0850	−0.0850	−0.0975
	(0.287)	(0.288)	(0.262)	(0.274)	(0.274)	(0.275)
wspdGround_l1	−0.310	−0.288	−0.354*	−0.589***	−0.589***	−0.600***
	(0.231)	(0.232)	(0.213)	(0.228)	(0.228)	(0.228)
dtp1000_G_l1	0.120***	0.119***	0.118***	0.103***	0.103***	0.105***
	(0.0394)	(0.0390)	(0.0375)	(0.0365)	(0.0365)	(0.0365)
dtp925_1000_l1	0.135***	0.137***	0.133***	0.119***	0.119***	0.120***
	(0.0365)	(0.0360)	(0.0349)	(0.0343)	(0.0343)	(0.0344)
dtp850_925_l1	0.0645	0.0641	0.0628	0.0375	0.0375	0.0387
	(0.0533)	(0.0531)	(0.0497)	(0.0428)	(0.0428)	(0.0428)
dtp700_850_l1	−0.0452	−0.0476*	−0.0426	−0.0322	−0.0322	−0.0306
	(0.0289)	(0.0285)	(0.0280)	(0.0299)	(0.0299)	(0.0298)
dtp500_700_l1	0.197	0.209	0.180	0.154	0.154	0.132
	(0.165)	(0.164)	(0.155)	(0.167)	(0.167)	(0.164)
wd_n_l1	0.339	0.372	0.288	−0.125	−0.125	−0.124
	(0.291)	(0.294)	(0.265)	(0.241)	(0.241)	(0.241)
wd_e_l1	0.416	0.446	0.370	0.0285	0.0285	0.0337
	(0.293)	(0.296)	(0.267)	(0.239)	(0.239)	(0.239)
wd_s_l1	0.525*	0.560*	0.472*	0.0713	0.0713	0.0791
	(0.293)	(0.295)	(0.266)	(0.237)	(0.237)	(0.237)
wd_w_l1	0.363	0.385	0.337	−0.0465	−0.0465	−0.0492
	(0.292)	(0.294)	(0.265)	(0.239)	(0.239)	(0.239)
wspdlow_dtp1000 _Gpos_l1	0.0174	0.0136	0.0229	0.0403	0.0403	0.0391
	(0.0903)	(0.0890)	(0.0862)	(0.0927)	(0.0927)	(0.0925)
wspdlow_dtp925 _1000pos_l1	0.0183	0.0499	−0.0356	−0.307	−0.307	−0.300
	(0.191)	(0.185)	(0.188)	(0.211)	(0.211)	(0.211)
wspdlow_dtp850 _925pos_l1	0.0860	0.0733	0.117	0.337	0.337	0.342
	(0.386)	(0.377)	(0.373)	(0.321)	(0.321)	(0.322)
wspdlow_l1	0.0298	0.0373	0.0134	−0.0302	−0.0302	−0.0312
	(0.0962)	(0.0955)	(0.0910)	(0.0963)	(0.0963)	(0.0960)

(*continued on next page*)

Table B.1 *(continued)*

VARIABLES	pm	pm	pm	pm	pm	pm
dtp1000_Gpos_l1	−0.0162	−0.0143	−0.0197	0.00633	0.00633	0.00417
	(0.0518)	(0.0516)	(0.0487)	(0.0455)	(0.0455)	(0.0456)
dtp925_1000pos_l1	−0.298**	−0.302**	−0.294**	−0.167	−0.167	−0.171
	(0.141)	(0.138)	(0.136)	(0.150)	(0.150)	(0.150)
dtp850_925pos_l1	−0.124	−0.118	−0.123	−0.199	−0.199	−0.205
	(0.267)	(0.262)	(0.259)	(0.204)	(0.204)	(0.204)
wspdGround_l2	0.206	0.245	0.131	0.00850	0.00850	0.0250
	(0.326)	(0.323)	(0.312)	(0.315)	(0.315)	(0.319)
dtp1000_G_l2	−0.0505	−0.0506	−0.0511	−0.0517	−0.0517	−0.0507
	(0.0343)	(0.0340)	(0.0325)	(0.0317)	(0.0317)	(0.0316)
dtp925_1000_l2	0.0790**	0.0787**	0.0787**	0.0793**	0.0793**	0.0763**
	(0.0372)	(0.0369)	(0.0352)	(0.0386)	(0.0386)	(0.0388)
dtp850_925_l2	−0.00464	−0.00876	0.000486	−0.0465	−0.0465	−0.0481
	(0.0415)	(0.0411)	(0.0397)	(0.0367)	(0.0367)	(0.0369)
dtp700_850_l2	−0.0173	−0.0133	−0.0260	−0.0707*	−0.0707*	−0.0722**
	(0.0372)	(0.0369)	(0.0348)	(0.0366)	(0.0366)	(0.0365)
dtp500_700_l2	0.0139	0.0238	−0.00875	−0.138	−0.138	−0.106
	(0.167)	(0.166)	(0.157)	(0.132)	(0.132)	(0.132)
wd_n_l2	0.0796	0.105	0.0193	0.250	0.250	0.245
	(0.240)	(0.246)	(0.211)	(0.220)	(0.220)	(0.221)
wd_e_l2	−0.0218	−0.00571	−0.0726	0.151	0.151	0.140
	(0.238)	(0.244)	(0.208)	(0.218)	(0.218)	(0.218)
wd_s_l2	0.115	0.133	0.0612	0.254	0.254	0.248
	(0.235)	(0.241)	(0.205)	(0.217)	(0.217)	(0.217)
wd_w_l2	0.180	0.200	0.115	0.320	0.320	0.309
	(0.243)	(0.248)	(0.214)	(0.222)	(0.222)	(0.222)
wspdlow_dtp1000 _Gpos_l2	0.0641	0.0633	0.0679	0.0250	0.0250	0.0244
	(0.0940)	(0.0936)	(0.0887)	(0.0894)	(0.0894)	(0.0895)
wspdlow_dtp925 _1000pos_l2	0.161	0.168	0.149	0.0684	0.0684	0.0703
	(0.197)	(0.192)	(0.192)	(0.188)	(0.188)	(0.188)
wspdlow_dtp850 _925pos_l2	0.648**	0.657**	0.638**	0.726***	0.726***	0.734***
	(0.271)	(0.265)	(0.264)	(0.239)	(0.239)	(0.244)
wspdlow_l2	0.0907	0.0998	0.0726	0.0404	0.0404	0.0427
	(0.114)	(0.113)	(0.109)	(0.103)	(0.103)	(0.103)
dtp1000_Gpos_l2	0.0539	0.0539	0.0579	0.0478	0.0478	0.0420
	(0.0442)	(0.0439)	(0.0415)	(0.0408)	(0.0408)	(0.0409)
dtp925_1000pos _l2	−0.667***	−0.670***	−0.656***	−0.582***	−0.582***	−0.576***
	(0.187)	(0.184)	(0.180)	(0.185)	(0.185)	(0.185)
dtp850_925pos_l2	−0.457	−0.463*	−0.434	−0.155	−0.155	−0.165
	(0.281)	(0.277)	(0.270)	(0.191)	(0.191)	(0.196)
wspdGroundsq	0.0433	0.0434	0.0440	0.0553	0.0553	0.0558
	(0.0660)	(0.0644)	(0.0646)	(0.0727)	(0.0727)	(0.0732)
dtp1000_Gsq	0.00952	0.0111	0.00679	0.00948	0.00948	0.00946
	(0.0169)	(0.0167)	(0.0160)	(0.0164)	(0.0164)	(0.0165)
dtp925_1000sq	0.0216***	0.0212***	0.0224***	0.0217***	0.0217***	0.0214***
	(0.00570)	(0.00573)	(0.00539)	(0.00540)	(0.00540)	(0.00540)
dtp850_925sq	0.000980	0.00186	−0.000452	0.000555	0.000555	0.000596
	(0.00601)	(0.00636)	(0.00515)	(0.00566)	(0.00566)	(0.00567)
dtp700_850sq	−0.00609	−0.00645	−0.00582	−0.00733	−0.00733	−0.00674
	(0.00523)	(0.00522)	(0.00490)	(0.00507)	(0.00507)	(0.00510)
dtp500_700sq	0.0174	0.0177	0.0164	0.00961	0.00961	0.00859
	(0.0144)	(0.0140)	(0.0138)	(0.0122)	(0.0122)	(0.0121)
wspdGroundsq_l1	0.0738	0.0672	0.0868	0.165**	0.165**	0.170**
	(0.0749)	(0.0755)	(0.0687)	(0.0719)	(0.0719)	(0.0720)
dtp1000_Gsq_l1	−0.0300*	−0.0309*	−0.0265	−0.00684	−0.00684	−0.00844
	(0.0177)	(0.0174)	(0.0168)	(0.0166)	(0.0166)	(0.0165)
dtp925_1000sq_l1	0.00506*	0.00503*	0.00517**	0.00453	0.00453	0.00432
	(0.00265)	(0.00259)	(0.00257)	(0.00316)	(0.00316)	(0.00319)
dtp850_925sq_l1	0.00533	0.00594	0.00365	−0.00126	−0.00126	−0.00121
	(0.00955)	(0.00979)	(0.00845)	(0.00650)	(0.00650)	(0.00652)
dtp700_850sq_l1	−0.0078*	−0.0081**	−0.0076*	−0.0066	−0.0066	−0.0067
	(0.0041)	(0.0041)	(0.0040)	(0.0043)	(0.0043)	(0.0043)
dtp500_700sq_l1	0.0147	0.0156	0.0134	0.0103	0.0103	0.00898
	(0.0113)	(0.0113)	(0.0107)	(0.0112)	(0.0112)	(0.0110)
wspdGroundsq_l2	−0.0955	−0.108	−0.0719	−0.0284	−0.0284	−0.0350
	(0.108)	(0.108)	(0.103)	(0.102)	(0.102)	(0.103)

(*continued on next page*)

Table B.1 *(continued)*

VARIABLES	pm	pm	pm	pm	pm	pm
dtp1000_Gsq_l2	0.0312*	0.0310*	0.0315*	0.0504***	0.0504***	0.0496***
	(0.0181)	(0.0180)	(0.0170)	(0.0168)	(0.0168)	(0.0168)
dtp925_1000sq_l2	0.000565	0.000496	0.000853	0.00275	0.00275	0.00253
	(0.00337)	(0.00332)	(0.00323)	(0.00483)	(0.00483)	(0.00494)
dtp850_925sq_l2	−0.0086	−0.0086	−0.0094*	−0.0094**	−0.0094**	−0.0091**
	(0.0058)	(0.0059)	(0.0052)	(0.0045)	(0.0045)	(0.0046)
dtp700_850sq_l2	0.00161	0.00226	0.000141	−0.00443	−0.00443	−0.00459
	(0.00548)	(0.00546)	(0.00513)	(0.00523)	(0.00523)	(0.00521)
dtp500_700sq_l2	0.000382	0.00109	−0.00114	−0.00845	−0.00845	−0.00642
	(0.0111)	(0.0110)	(0.0105)	(0.00903)	(0.00903)	(0.00901)
wspdGroundcb	−0.00353	−0.00349	−0.00383	−0.00383	−0.00383	−0.00392
	(0.00647)	(0.00632)	(0.00630)	(0.00692)	(0.00692)	(0.00699)
dtp1000_Gcb	−0.00119	−0.00113	−0.00127	−0.00158	−0.00158	−0.00150
	(0.00260)	(0.00263)	(0.00238)	(0.00241)	(0.00241)	(0.00243)
dtp925_1000 cb	0.00164	0.00156	0.00171*	0.00268***	0.00268***	0.00267***
	(0.00106)	(0.00105)	(0.00101)	(0.000984)	(0.000984)	(0.000984)
dtp850_925 cb	0.000372	0.000460	0.000268	−0.000528	−0.000528	−0.000578
	(0.000818)	(0.000836)	(0.000747)	(0.000735)	(0.000735)	(0.000736)
dtp700_850 cb	−3.45e-05	−5.31e-05	−2.54e-05	−8.41e-05	−8.41e-05	−6.57e-05
	(0.000245)	(0.000244)	(0.000230)	(0.000233)	(0.000233)	(0.000234)
dtp500_700 cb	0.000380	0.000383	0.000360	0.000211	0.000211	0.000190
	(0.000312)	(0.000305)	(0.000300)	(0.000259)	(0.000259)	(0.000257)
wspdGroundcb_l1	−0.00471	−0.00406	−0.00598	−0.0137**	−0.0137**	−0.0142**
	(0.00740)	(0.00748)	(0.00675)	(0.00681)	(0.00681)	(0.00683)
dtp1000_Gcb_l1	0.000814	0.000897	0.000457	−0.00179	−0.00179	−0.00157
	(0.00250)	(0.00249)	(0.00235)	(0.00235)	(0.00235)	(0.00233)
dtp925_1000 cb_l1	−0.0019**	−0.0019**	−0.0018**	−0.0018**	−0.0018**	−0.0019**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
dtp850_925 cb_l1	0.000292	0.000413	4.09e-05	−3.93e-05	−3.93e-05	−4.55e-05
	(0.00105)	(0.00106)	(0.000955)	(0.000814)	(0.000814)	(0.000819)
dtp700_850 cb_l1	−0.000300	−0.000316	−0.000291	−0.000262	−0.000262	−0.000269
	(0.000206)	(0.000204)	(0.000196)	(0.000200)	(0.000200)	(0.000202)
dtp500_700 cb_l1	0.000315	0.000337	0.000281	0.000195	0.000195	0.000171
	(0.000255)	(0.000254)	(0.000240)	(0.000244)	(0.000244)	(0.000241)
wspdGroundcb_l2	0.00987	0.0110	0.00776	0.00390	0.00390	0.00455
	(0.0106)	(0.0106)	(0.0100)	(0.00971)	(0.00971)	(0.00990)
dtp1000_Gcb_l2	−0.0052*	−0.0052*	−0.0052**	−0.0083***	−0.0083***	−0.0082***
	(0.0028)	(0.0028)	(0.0026)	(0.0026)	(0.0026)	(0.0027)
dtp925_1000 cb_l2	−0.00141*	−0.00140*	−0.00139*	−0.000961	−0.000961	−0.000940
	(0.000847)	(0.000837)	(0.000808)	(0.000989)	(0.000989)	(0.000999)
dtp850_925 cb_l2	−0.00103	−0.000957	−0.00123*	−0.000596	−0.000596	−0.000546
	(0.000805)	(0.000814)	(0.000748)	(0.000707)	(0.000707)	(0.000712)
dtp700_850 cb_l2	0.000137	0.000168	6.81e-05	−8.79e-05	−8.79e-05	−9.45e-05
	(0.000257)	(0.000256)	(0.000241)	(0.000236)	(0.000236)	(0.000235)
dtp500_700 cb_l2	−0.0000	−0.0000	−0.0000	−0.0001	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant				2.723**	2.723**	2.701**
				(1.303)	(1.303)	(1.287)
Month FE	YES	YES	YES	YES	YES	YES
DOW FE	YES	YES	YES	YES	YES	YES
Weather	YES	YES	YES	YES	YES	YES
Hedonic Attributes	YES	YES	YES	YES	YES	YES
Kleibergen-Paap F statistics	6.89	7.21	7.48	5.09	5.09	5.01
Cragg-Donald Wald F statistics	966.82	612.76	311.32	4.97	4.97	4.88
Observations	108,358	68,956	37,911	718	718	715
R-squared	0.787	0.788	0.786	0.771	0.771	0.772

This table reports the first stage regression results for our IV estimation. According to the equation in footnote [17], we have included all the exogenous variables in the first stage regressions including the fixed effects and control variables in the OLS estimations. For the thermal inversion and wind variables, we also included their squared and cubed terms together with the first and second order lags as well as the interaction terms. Note that the literature has not reached a consensus on the use of first stage F value when the standard errors are clustered.

wspd: wind speed; dtp##_***: pressure difference between altitude ## and altitude **; l#: lag of order #; sq: squared term; cb: cubed term; wspdlow is a dummy variable that takes the value of 1 if the ground wind speed is lower than 1 and otherwise 0; north, east, south, and west are dummy variables for wind directions.

* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table B.2
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	0.0021	0.0017**	0.0018**
	(0.0017)	(0.0025)	(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	107,956	107,956	107,383	107,383
R-squared	0.150	0.150	0.335	0.335

Note: Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table B.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	0.0016**	0.0015**		
	(0.0007)	(0.0007)		
AQI/100			0.0014*	0.0012
			(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	108,514	108,514	106,593	105,017
R-squared	0.334	0.335	0.334	0.335

Note: Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table B.4
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	0.0009	0.0008*		
	(0.0008)	(0.0004)		
AQI/100			0.0011	0.0009**
			(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	98,545	98,545	98,545	98,545
R-squared	0.337	0.337	0.337	0.337

Note: Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table B.5
The Impact of Air Pollution on Transacted Prices (*per sqm*): Controlling for Policy Changes and Payment Methods.

Variables	(1) Ln (Unit Price)	(2) Ln (Unit Price)	(3) Ln (Unit Price)	(4) Ln (Unit Price)
$PM_{2.5}/100$	0.0017**	0.0018***	0.0019***	0.0018**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Policy 1			−0.0158***	−0.0164*
			(0.0058)	(0.0092)
Policy 2			0.0121***	0.0111***
			(0.0023)	(0.0023)
Policy 3			0.0067***	0.0068***
			(0.0020)	(0.0020)
Policy 4			−0.0006	−0.0007
			(0.0028)	(0.0027)
Cash Payment	−0.0004			−0.0004
	(0.0010)			(0.0010)
$PM_{2.5}$ on Reg Day		−0.0000		0.0000
		(0.0000)		(0.0000)
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	105,013	108,507	108,514	105,009
R-squared	0.334	0.334	0.334	0.334

Note: Over our sampling period, we collect four policy changes to create four dummy variables.
Policy 1: Oct 30 2014. The central bank loosened the requirement on loan mortgage.
http://www.gov.cn/xinwen/2014-09/30/content_2759366.htm.
Policy 2: March 30 2015. The central bank lowered down payment requirement for second unit.
http://www.cbrc.gov.cn/chinese/home/docDOC_ReadView/A22257A770B649F9BC0664F5719CC1EE.html.
Policy 3: August 19 2015. Removed restrictions on foreign buyers and investors.
http://www.mohurd.gov.cn/wjfb/201508/t20150828_224060.html.
Policy 4: September 14 2015. Lowered down payment requirement by Housing Provident Fund.
http://www.zzz.gov.cn/html/xwzx/tzgg/10582.html.
For all the four policy dummy variables, they take value 1 after the policy implementation and 0 before.
Cash payment is a dummy variable that takes value 1 for cash buyers and 0 otherwise.
$PM_{2.5}$ on Reg Day is the $PM_{2.5}$ level on the date that the buyer register in the broker's system.
Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table B.6
The Impact of Air Pollution on Transacted Prices (*per sqm*): Beijing, Shanghai, and Guangzhou.

VARIABLES	(1) Ln (Unit Price)	(2) Ln (Unit Price)	(3) Ln (Unit Price)	(4) Ln (Unit Price)
$PM_{2.5}/100$	0.0027***	0.0028***		
	(0.0008)	(0.0008)		
$PM_{2.5}$ Level 2			0.0008	0.0010
			(0.0014)	(0.0014)
$PM_{2.5}$ Level 3			0.0048***	0.0048***
			(0.0016)	(0.0016)
$PM_{2.5}$ Level 4			0.0039*	0.0042**
			(0.0021)	(0.0021)
$PM_{2.5}$ Level 5			0.0034*	0.0034*
			(0.0020)	(0.0020)
$PM_{2.5}$ Level 6			0.0064**	0.0067**
			(0.0028)	(0.0028)
$PM_{2.5}$ Level 7			0.0082**	0.0082**
			(0.0033)	(0.0033)
Shanghai	−0.745***	−0.745***	−0.744***	−0.744***
	(0.119)	(0.119)	(0.119)	(0.119)
Guangzhou	−0.169	−0.169	−0.169	−0.168
	(0.111)	(0.111)	(0.111)	(0.111)
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	129,001	129,001	129,001	129,001
R-squared	0.188	0.188	0.188	0.188
Number of c_name	8537	8537	8537	8537

Note: Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table B.7
Balancing Tests of House Characteristics.

Mean Value	$PM_{2.5}$ Level 1	$PM_{2.5}$ Level 2	$PM_{2.5}$ Level 3	$PM_{2.5}$ Level 4	$PM_{2.5}$ Level 5	$PM_{2.5}$ Level 6	$PM_{2.5}$ Level 7
Area	82.3871	82.3794	82.3105	82.0496	81.9333	82.7637	81.8737
Observations	31,814	40,426	23,700	10,235	14,815	7388	1964
Floor	7.2353	7.2245	7.1975	7.2021	7.292	7.1743	7.2704
Observations	31,814	40,426	23,700	10,235	14,815	7388	1964
Distance to CBD	13319.96	13367.53	13254.21	13218.12	13401.99	13390.17	13165.7
Observations	28,852	36,674	21,497	9331	13,417	6649	1771
Number of Bedrooms	2.0092	2.0068	2.0107	2.012	2.0047	2.016	2.014
Observations	31,811	40,425	23,697	10,234	14,815	7388	1964
North-south Exposure	0.4771	0.4785	0.478	0.4854	0.474	0.4809	0.4822
Observations	31,814	40,426	23,700	10,235	14,815	7388	1964
Face South	0.2556	0.2505	0.2588	0.2546	0.2651	0.2549	0.2668
Observations	31,814	40,426	23,700	10,235	14,815	7388	1964
Tower Block	0.2515	0.2489	0.2503	0.2485	0.2491	0.2485	0.2546
Observations	31,814	40,426	23,700	10,235	14,815	7388	1964

Note: * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. All t-tests are performed in relative to level 1.

Table B.8
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)
$PM_{2.5}/100$	0.0019	0.0013		
	(0.0012)	(0.0011)		
AQI/100			0.0010	0.0007
			(0.0013)	(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	37,962	37,962	37,299	36,740
R-squared	0.302	0.303	0.303	0.306

Note: Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
AQI data was only available starting in 2014.

Table B.9
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)
$PM_{2.5}/100$	0.0015*	0.0016*		
	(0.0009)	(0.0009)		
AQI/100			0.0018*	0.0017*
			(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	69,061	69,061	67,804	66,777
R-squared	0.357	0.358	0.356	0.357

Note: Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
AQI data was only available starting in 2014.

Table B.10
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	0.0029*	0.0030***	−0.00021	−0.0000
	(0.0011)	(0.0011)	(0.0014)	(0.0014)
$PM_{2.5}$ Level 3	0.0050***	0.0049***	0.0015	0.0017
	(0.0014)	(0.0014)	(0.0018)	(0.0018)
$PM_{2.5}$ Level 4	0.0050***	0.0051***	0.0034	0.0037
	(0.0019)	(0.0018)	(0.0024)	(0.0024)
$PM_{2.5}$ Level 5	0.0034*	0.0034*	0.0013	0.0011
	(0.0020)	(0.0020)	(0.0027)	(0.0026)
$PM_{2.5}$ Level 6	0.0075***	0.0077***	0.0040	0.0036
	(0.0026)	(0.0026)	(0.0031)	(0.0031)
$PM_{2.5}$ Level 7	0.0068*	0.0071*	0.0054	0.0048
	(0.0038)	(0.0037)	(0.0057)	(0.0058)
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	69,061	69,061	37,962	37,962
R-squared	0.357	0.357	0.301	0.302

Note: Robust standard errors are two way clustered at the community-day level.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.
$PM_{2.5}$ cutoff points are 35, 75, 115, 150, 250, and 350.

Table B.11
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	0.111***	0.0394	0.112**	0.0280	0.104**	0.0266
	(0.0397)	(0.0333)	(0.0480)	(0.0380)	(0.0428)	(0.0370)
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	0.741	0.776	0.748	0.778	0.785	0.808

Note: Robust standard errors are reported in the parentheses.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table B.12
The Impact of Air Pollution (AQI) on Home Buyers' Sentiments.

Variables	Baidu Index			Sofun
	(1) Lianjia	(2) Buy house	(3) Soufang	(4) Soufun Web Click
AQI/100	0.020*	0.017*	0.029**	0.021***
	(0.013)	(0.009)	(0.012)	(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: Robust standard errors are reported in the parentheses.
* significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

Table B.13
The Impact of Air Pollution ($PM_{2.5}$) on Transacted Prices (Total Price).

Variables	OLS Ln (Total Price)	OLS Ln (Total Price)	2SLS Ln (Total Price)	OLS Ln (Total Price)	OLS Ln (Total Price)
$PM_{2.5}/100$	0.0018***	0.0018***	0.0032***		
	(0.0007)	(0.0007)	(0.0009)		
$PM_{2.5}$ Level 2				0.0014	0.0015*
				(0.0009)	(0.0009)
$PM_{2.5}$ Level 3				0.0032***	0.0033***
				(0.0012)	(0.0012)
$PM_{2.5}$ Level 4				0.0039**	0.0040**
				(0.0016)	(0.0016)
$PM_{2.5}$ Level 5				0.0021	0.0021
				(0.0017)	(0.0017)
$PM_{2.5}$ Level 6				0.0054**	0.0055**
				(0.0023)	(0.0023)
$PM_{2.5}$ Level 7				0.0065**	0.0065**
				(0.0031)	(0.0030)
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	108,514	108,514	108,358	108,514	108,514
R-squared	0.866	0.866	0.866	0.866	0.866

Notes: Robust 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 6.89 in Column 3.
The Cragg-Donald Wald F statistic is 966.82 in Column 3. Threshold values for maximal IV relative bias of 5%: 21.12; 10%: 10.91; 20%: 5.69. Note that these threshold values only apply to the non clustered standard errors cases. $PM_{2.5}$ 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.

C. Figure

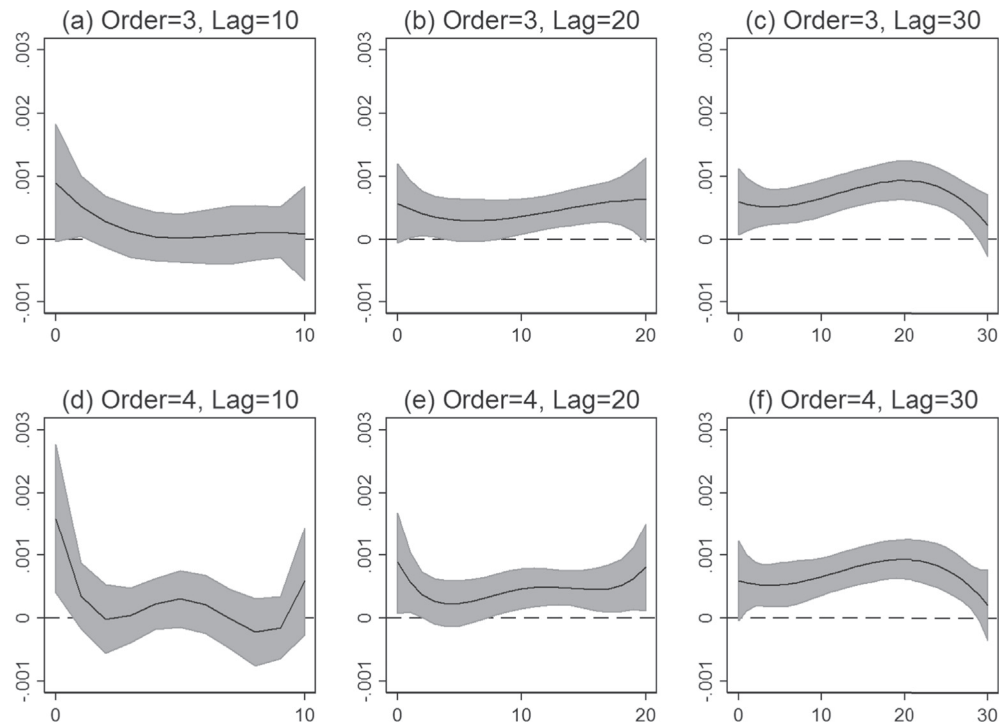

Fig. C.1 The Impact of Air Pollution on Unit Price: Various Order-lag Specifications. *Note:* Regression coefficients with 95% confidence interval.

References

Almon, S., 1965. The distributed lag between capital appropriations and expenditures. Econometrica: J. Econ. Soc. 33 (1), 178–196.
Azar, O.H., 2007. Relative thinking theory. J. Soc. Econ. 36 (1), 1–14.
Barwick, P.J., Li, S., Rao, D., Zahur, N.B., 2017. Air Pollution, Health Spending and Willingness to Pay for Clean Air in China. Working Paper.
Bordalo, P., Gennaioli, N., Shleifer, A., 2012. Salience theory of choice under risk. Q. J. Econ. 127 (3), 1243–1285.
Bordalo, P., Gennaioli, N., Shleifer, A., 2013a. Salience and consumer choice. J. Polit. Econ. 121 (5), 803–843.
Bordalo, P., Gennaioli, N., Shleifer, A., 2013b. Salience and asset prices. Am. Econ. Rev. 103 (3), 623–628.
Bushong, B., Rabin, M., Schwartzstein, J., 2015. A Model of Relative Thinking. Unpublished manuscript. Harvard University, Cambridge, MA.
Busse, M.R., Pope, D.G., Pope, J.C., Silva-Risso, J., 2015. The psychological effect of weather on car purchases. Q. J. Econ. 130 (1), 371–414.
Cameron, C.A., Miller, D.L., 2015. A practitioner's guide to cluster-robust inference. J. Hum. Resour. 50 (2), 317–372.
Chang, T.Y., Huang, W., Wang, Y., 2017. Something in the air: projection bias and the demand for health insurance. Rev. Econ. Stud. forthcoming.
Chay, K.Y., Greenstone, M., 2005. Does air quality matter? Evidence from the housing market. J. Polit. Econ. 113 (2), 376–424.
Chen, X., Zhang, X., Zhang, X., 2016. Smog in our brains: the impact of short-term and long-term exposures to air pollution on cognitive performance. In: 6th Biennial Conference of the American Society of Health Economists. Ashecon.
Chen, Y., Jin, G.Z., Kumar, N., Shi, G., 2012. Gaming in air pollution data? lessons from China. B. E. J. Econ. Anal. Policy 12 (3) 1935–1682.
Chen, Y., Ebenstein, A., Greenstone, M., Li, H., 2013a. Evidence on the impact of sustained exposure to air pollution on life expectancy from China's huai river policy. Proc. Natl. Acad. Sci. Unit. States Am. 110 (32), 12936–12941.
Chen, Y., Jin, G.Z., Kumar, N., Shi, G., 2013b. The promise of Beijing: evaluating the impact of the 2008 Olympic games on air quality. J. Environ. Econ. Manag. 66 (3), 424–443.
Chew, S.H., Huang, W., Li, X., 2017. Haze and Decision Making: A Natural Laboratory Experiment. Working Paper.
Conlin, M., O'Donoghue, T., Vogelsang, T.J., 2007. Projection bias in catalog orders. Am. Econ. Rev. 97 (4), 1217–1249.
Dessaint, O., Matray, A., 2017. Do managers overreact to salient risks? Evidence from hurricane strikes. J. Financ. Econ. 126 (1), 97–121.
Fang, H., Gu, Q., Xiong, W., Zhou, L.-A., 2015. Demystifying the Chinese housing boom. In: NBER Macroeconomics Annual 2015, vol. 30. University of Chicago Press.
Graff Zivin, J., Neidell, M., 2012. The impact of pollution on worker productivity. Am. Econ. Rev. 102 (7), 3652–3673.
Hastings, J.S., Shapiro, J.M., 2013. Fungibility and consumer choice: evidence from commodity price shocks. Q. J. Econ. 128 (4), 1449–1498.
He, J., Liu, H., Salvo, A., 2016. Severe Air Pollution and Labor Productivity: Evidence from Industrial Towns in china. working paper.
Heyes, A., Neidell, M., Saberian, S., 2016. The Effect of Air Pollution on Investor Behavior: Evidence from the S&P 500. NBER working paper, w22753.
Ito, K., Zhang, S., 2016. Willingness to Pay for Clean Air: Evidence from the Air Purifier Markets in China. Technical report.
Kahneman, D., 2003. Maps of bounded rationality: psychology for behavioral economics. Am. Econ. Rev. 93 (5), 1449–1475.
Kőszegi, B., Szeidl, A., 2012. A model of focusing in economic choice. Q. J. Econ. 128 (1), 53–104.
Li, J.J., Massa, M., Zhang, H., Zhang, J., 2017. Behavioral Bias in Haze: Evidence from Air Pollution and the Disposition Effect in China. Working Paper.
Lian, C., Ma, Y., Wang, C., 2017. Low Interest Rates and Risk Taking: Evidence from Individual Investment Decisions. working paper.
Liu, H., Salvo, A., 2018. Severe air pollution and child absences when schools and parents respond. J. Environ. Econ. Manag. 92 (8), 300–330.
Qin, Y., Zhu, H., 2018. Run away? Air pollution and emigration interests in China. J. Popul. Econ. 31 (1), 235–266.
Read, D., Loewenstein, G., Rabin, M., Keren, G., Laibson, D., 1999. Choice bracketing. In: Elicitation of Preferences. Springer, pp. 171–202.
Stafford, T.M., 2015. Indoor air quality and academic performance. J. Environ. Econ. Manag. 70, 34–50.
Sun, C., Kahn, M.E., Zheng, S., 2017. Self-protection investment exacerbates air pollution exposure inequality in urban China. Ecol. Econ. 131, 468–474.
Thaler, R.H., 1999. Mental accounting matters. J. Behav. Decis. Making 12 (3), 183.
Viard, B.V., Fu, S., 2015. The effect of Beijing's driving restrictions on pollution and economic activity. J. Publ. Econ. 125, 98–115.
Zhang, J., Mu, Q., 2017. Air pollution and defensive expenditures: evidence from particulate-filtering facemasks. J. Environ. Econ. Manag. (in press).
Zhang, X., Zhang, X., Chen, X., 2017. Happiness in the air: how does a dirty sky affect mental health and subjective well-being? J. Environ. Econ. Manag. 85, 81–94.
Zhen, H., Lv, P., 2011. Wo guo cheng zhen hua jin cheng zhong de cheng shi zhu fang zu lin ti xi jian she yan jiu. Construct. Econ. (2), 66–70 (in Chinese).