The Value of Better Air Quality: Evidence from Beijing Housing Market

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Abstract

To better estimate the possible benefits of environmental protection policies, it is crucial to evaluate the value of better air quality. Given that air quality is a non-marketable amenity, we use house prices to infer the value people place on air quality. We studied the relationship between house prices and PM 2.5 (a measure of harmful particulates in the air) in Beijing, one of the worst affected areas by air pollution in China. We control for house characteristics, neighborhood characteristics, and time-fixed effects to isolate the impact of air pollution on housing prices. Our result suggests that when the number of unhealthy days in 60 days before the transaction increases by one, the housing prices will decrease by 0.2 percent. This result is robust to sensitivity checks and omitted variables bias. Furthermore, our sensitivity tests show that wealthier households are willing to pay a higher housing price for better air quality. The results help to estimate the impact of air quality and its changes in economic development and provide a reference for the development of relevant policies.

I Introduction

Air quality can be an issue that not only matters to residents in certain areas but has also raised more concerns from the Chinese government in recent years. Studies have shown that long-term exposure to a high PM 2.5 environment will increase the risk of lung cancer and heart disease. People with medical conditions such as asthma are more sensitive to PM 2.5 [NPA21]. Due to too much emphasis on economic growth in China, air pollution has become a major environmental problem. Figure 1 illustrates the relationship between GDP per capita and the PM 2.5 from 1990 to 2016. As China's economy has taken off, air quality has deteriorated rapidly.

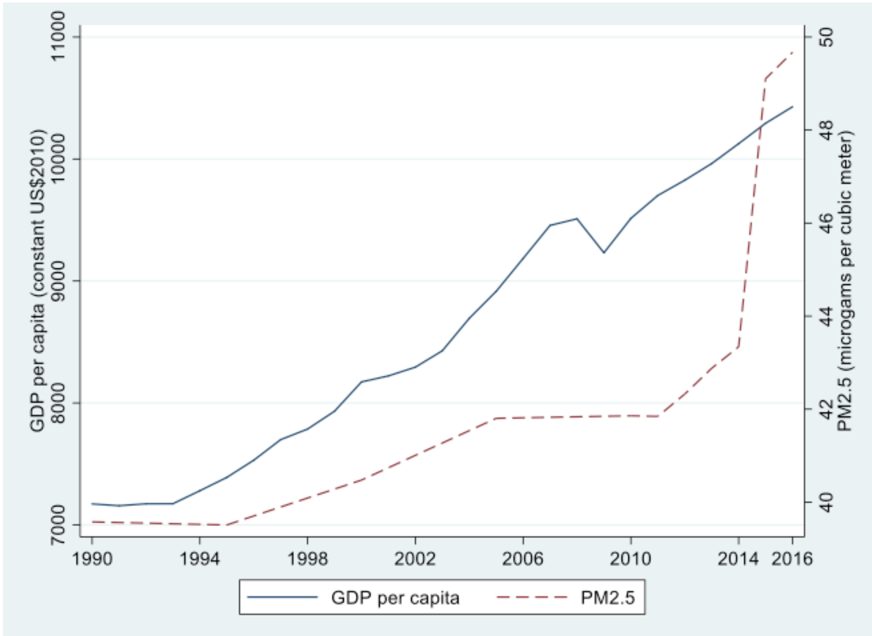

FIGURE 1: China's GDP per capita and PM 2.5 from 1990 to 2016

Since there is no direct market for air transactions, researchers have studied the relationship between air pollution and property value to infer people's willingness to pay for better air quality. Chay and Greenstone [CG05] adopted the hedonic approach and studied the effect of total suspended particulates (TSPs) on the median housing price of each American county. They found that a one microgram per cubic meter decrease in total suspended particulates will increase the median housing price by 0.2 to 0.4 percent. This estimate represents the willingness to pay for better air quality for the entire US population with county-level data. However, it underestimates the variation of individual preference because the study does not control for taste heterogeneity within each county. Other studies corroborate this pitfall of using macro-level data. Smith and Huang [SH95] reported the marginal willingness to pay (MWTP) for reducing particulate matter from the hedonic property value model. Their findings suggest that the estimated MWTP method can lead to severe mistakes due to substantial local conditions variations.

Other researchers have looked at local-level real estate markets. Anderson and Crocker [AJC71] quantified the residential value of the property given air quality at a theoretical level. They maximized utility function for both renter and owner and found the empirical result that air quality has a positive relationship with residential property value. Tang and Niemeier [TN21] utilized a spatial lag model with an instrumental variable method to consider spatial autocorrelation and endogeneity effects between housing prices and air pollution in the Bay area. Surprisingly, their result indicates a positive relationship between air pollution and housing prices. Qin et al. [QWY19] also found a positive relationship by measuring the immediate effect of air pollution on a house-buying decision. However, it takes time for buyers to go from viewing to buying a house, so considering only the impact of pollution level on the house price on the day of the transaction cannot fully represent the actual decision-making process.

To avoid the pitfalls of previous studies, we study the real estate market in Beijing's urban area and construct quantitative indicators based on the home closing cycle using the number of days of air quality rating. Firstly, all observations come from the urban area of Beijing, so there is no variation in laws and regulations. There are also multiple air pollution monitoring centers to provide accurate PM 2.5 values for the closest house. Secondly, the number of unhealthy days before the transaction captures the air quality when buyers make their decisions. Our result indicates that the housing price will decrease by 0.16 percent for one more unhealthy day during 60 days before the transaction. This finding elucidates how people value better air quality, which helps policymakers evaluate environmental policies. In addition, our research highlights that better air quality not only improves people's health but also increases property values.

The rest of the paper is structured as follows: Section II presents the methodology; Section III describes the data and summary statistics; Section IV presents the results and sensitivity tests; Section V presents the conclusions.

II Methodology

The hedonic pricing method is widely used to infer air premium from variations in housing prices. It involves houses with different characteristics and consumers with heterogeneous tastes. Consumers who have the same tastes and wealth will attain the same level of utility in equilibrium. We adopt the hedonic price function for our estimation, in which the housing price is a function of the house characteristics, the district characteristics, air pollution, and fixed effects. The equation of interest is as follows:

$$ln(price) = \alpha + \beta N + \gamma H + \delta D + \eta F \tag{1}$$

where the price is the housing price per square meter of each observation. N is the number of unhealthy days in the two months before the house is traded. H is the characteristics of the house. D is the district where the house is located. F is the year dummy.

The advantages of our study are twofold: Firstly, by limiting our sample to the Beijing urban area, we can control the variation in laws and regulations. Detailed house-level data are also available for Beijing urban areas. We can control house characteristics and district characteristics to isolate our focus on the relationship between housing price and air quality. In addition, there are nine different air pollution monitoring sites located in populated Beijing urban areas to provide accurate air pollution indicators for every urban community. Therefore, we control the taste heterogeneity of the area under study and avoid underestimating the variation in individual preferences. Secondly, We take the buyer's decision making into account by looking at air quality in 60 days before the transaction. Therefore, our model can accurately study people's preferences for air quality.

III Data and Summary Statistics

In this paper, we collect hourly PM 2.5 data from 9 air quality monitoring sites obtained from the Beijing Municipal Environmental Monitoring Center from 2013 to 2017 and merge it with Beijing's second-hand house transaction information and weather conditions to obtain a detailed dataset. We choose Beijing as a study sample due to its geographic, climatic, economic, and social factors. First, Beijing's air quality varies widely in space and time. Second, Beijing has a nationally notable market for second-hand house transactions: residential transactions in the city's six districts have been dominated by second-hand houses in recent years. Buyers and sellers can cover more of both sides in the bargaining process, especially the buyer's perception of the surrounding air quality during field visits. The bargaining process for second-hand homes is also more complete than for selling new and term homes. Finally, in Beijing, as the capital city, air quality improvement and regulation are among the policy targeting priorities, and its environmental policies are implemented more frequently than in other regions.

III.1 PM 2.5 Data

Previous research has primarily focused on national data, comparing air quality in various cities. Even within the same city, there are substantial differences in air quality. For example, the difference in air quality between the north and the south of Beijing is very significant. Beijing's heavy industries are concentrated in the south, producing many pollutants, while the Yanshan Mountains in the north block some of the pollutants. Meanwhile, the air quality in Beijing exhibits distinct seasonal patterns. The boxplot of the monthly trend of PM 2.5 in Beijing is depicted in Figure 2. Overall, PM 2.5 is high in the autumn and winter but low in the spring and summer. Even within the same city, houses sold in different districts and on different dates generate variation in air quality for our analysis.

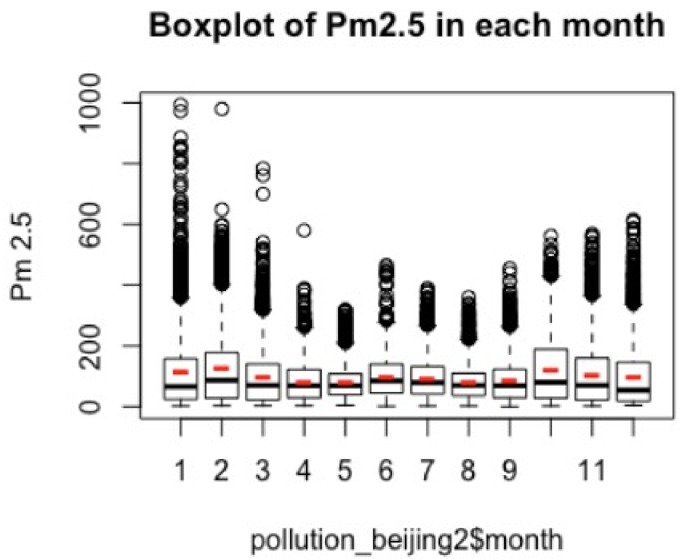

FIGURE 2: Boxplot of monthly trend of PM 2.5 in Beijing from 2013 to 2017

Our study only focuses on urban areas due to limited PM 2.5 monitoring sites in the suburbs. In this way, we could also avoid the heterogeneity in the laws and regulations. We characterize urban areas as the area bounded by the fifth ring road. FIGURE 3 shows the map of the different PM2.5 monitoring sites scattered in urban Beijing.

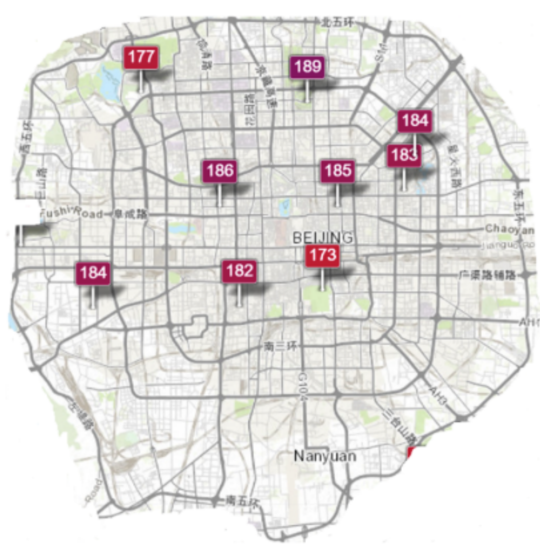

FIGURE 3: Locations of 9 Air Pollution Monitoring Sites in Beijing Urban Area

In order to get an estimation of daily PM 2.5 value, we plot the hourly PM 2.5 changes in each month. As shown in FIGURE 4, PM 2.5 tends to be lower in the middle of the day and higher at night. The variation is also vastly different in different months. Therefore, using the PM 2.5 value of a particular hour as daily value is biased, so we use the average of the hourly PM 2.5 observations for each day to characterize the air quality. Based on the air quality index by the U.S. Department of State Air Quality Monitoring Program, the level of PM 2.5 concentration at 0-50 is considered as good; 51-100 is moderate; 101-150 is unhealthy for sensitive groups; 150-200 is unhealthy; 201-300 is very unhealthy; 301-500 is hazardous. Therefore, we can categorize the average level of PM 2.5 concentration greater than 100 as unhealthy to make further analysis [CJZ07].

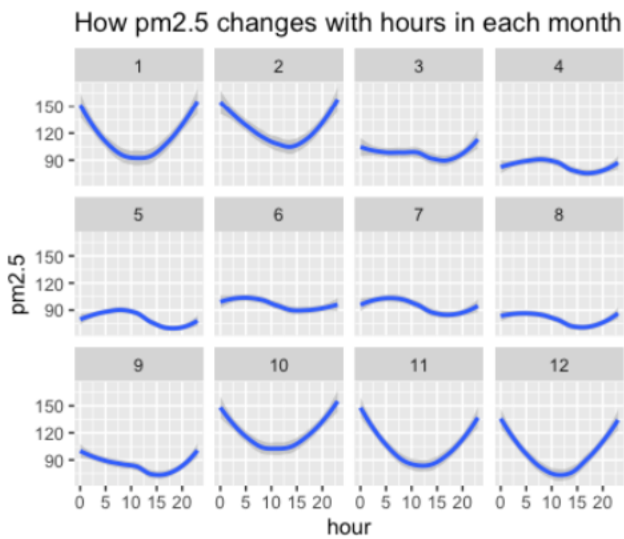

FIGURE 4: Hourly PM 2.5 Changes in Each Month

III.2 House Level Data

The house level data comes from the largest real estate brokerage firm in Beijing, and it occupies 60 percent of Beijing's real estate brokerage market. The dataset contains detailed information on 179,558 houses from 2013 to 2017. All houses are located in six urban districts: Xicheng, Dongcheng, Chaoyang, Haidian, Fengtai, and Shijingshan. These houses spread out across the city and are sufficient to represent Beijing's entire urban area's real estate market. The richness of this dataset helps us control the variation in house characteristics and district characteristics. Therefore, we can focus on the relationship between housing prices and air pollution.

After we have the air pollution and the house-level datasets, we match each house to the closest air pollution test center. The data we collected shows that it takes an average of about one to two months (mean 45 days, standard deviation 28 days) for a home to close, during which time home buyers get to know the house and its surroundings through on-site viewing and form a rough price range based on that. Based on this, we select 60 days before the transaction as the closing cycle of the house, and it is sufficient to capture the air quality when buyers are making their decisions. Lastly, we merge the number of unhealthy days in the 60 days before the transaction to each house.

III.3 Summary Statistics

The full dataset contains 179,151 houses in six districts within Beijing urban area. Table 1 shows the summary statistics. The mean housing price per square meter is 48,869 RMB with a standard deviation of 19,898 RMB. The mean total house price is 3,833,879 RMB with a standard deviation of 2,322,539 RMB. The mean number of unhealthy days in the two months before the house was traded is 17 days with a standard deviation of 7 days. The mean average PM 2.5 concentration in 60 days is 82, with a standard deviation of 23. We obtain general information such as the transaction date and how many days the house was listed on the market. The mean of active days on the market is 45 days with a standard deviation of 28 days. In addition, We use house-level variables to control for heterogeneity in people's tastes. These variables include the square meters of the house, number of living rooms and bathrooms, if there is a kitchen, which floor the apartment is on, construction time, if there are elevators in the building, if the owner has the property for less than five years, the district in which the house is located and if there is a subway station in the community.

IV Results

In this section, we first obtain the direct impact of the number of unhealthy days 60 days before the transaction on housing prices. Then we add more control variables to test the significance of the regression coefficients. To compare with previous studies, we also use the average PM 2.5 concentration 60 days before the transaction as a proxy for air quality and compare the regression results of the two different air quality indicators. Secondly, we examine the differences in willingness to pay for clean air among households of varying wealth by categorizing total and average housing prices into several groups. Finally, we build instrumental variables to run a sensitivity test.

IV.1 The Impact of Air Quality on Housing Price

Since people may not sense air pollution very acutely, a slight rise or decrease in average daily PM 2.5 may not accurately impact people's perceptions of pollution. As a result, house buyers may not be sensitive to the average concentration of air pollutants near the house but may instead have a strong impression when the air quality is extremely good or terrible. We, therefore, decide to use the number of unhealthy days in the standard air quality rating to represent people's perceptions of air quality. However, no studies have been conducted to determine how long home buyers will consider air quality. This time period should generally

Table 1: Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
price	179,151	48,869.400	19,898.740	1	156,250
totalPrice	179,151	3,833,879.000	2,322,539.000	115.200	60,000,072.000
unhealthy60	179,151	17.260	7.044	2	35
avgpm60	179,151	81.574	23.775	41.920	156.288
DOM	92,408	45.118	28.002	1	1,677
square	179,151	80.102	36.555	6.900	922.700
livingRoom	179,150	1.974	0.760	0	9
drawingRoom	179,150	1.143	0.508	0	5
kitchen	179,151	0.996	0.093	0	4
bathRoom	179,150	1.163	0.415	0	7
floor	179,150	14.034	7.924	1	63
constructionTime	168,230	1,998.036	9.145	1,914	2,016
elevator	179,150	0.618	0.486	0	1
fiveYearsProperty	179,150	0.701	0.458	0	1
subway	179,150	0.661	0.473	0	1
district	179,151	6.445	2.670	1	10
Year	179,151	2,015.143	1.061	2,013	2,017

start when the prospective house buyer begins to tour the property and end on the transaction date. However, because we don't have the exact variable in our data, we decide to utilize DOM (active days on the market). It describes the time period from when a house is listed to the time it is sold, which could capture the procedure of house buyers visiting a house in person and making the final decision. Based on the mean DOM (45 days), we select 60 days as our basegroup, and run regressions of the natural log of price per meter on the number of unhealthy days with different control variables.

Table 2 shows the regression results of the model we proposed. Without any control variables, column (1) shows the relationship between air pollution and house prices. The result indicates that the house price will drop by 0.1 percent for one more unhealthy day 60 days before the transaction. From column (2) to column (4), we gradually add controlling variables such as housing characteristics, district characteristics, and year dummy variables. The results in column (2) align with previous studies on housing prices. The number of living rooms and bathrooms positively correlated with higher housing prices. Having a kitchen, an elevator, and a subway station near the house also raises the value of a house. The house price is negatively correlated with the age of the building, the number of floors, and the square footage of the house. Since the average housing price in Beijing is significantly higher than in other cities, smaller homes are more affordable, which drives up the price. In columns (3) and (4), the coefficient of the number of unhealthy days rises to 0.2 percent. Column (4) suggests that air pollution has a more negative impact on housing prices after controlling all variables. For one more unhealthy day 60 days before the transaction, the housing price will decrease by 0.2 percent.

To compare with previous studies, we also use the average pm 2.5 concentration 60 days before the transaction as an air quality indicator. Table 3 shows the effect of average PM 2.5 concentration 60 days before transaction on house prices. We gradually add control variables, just as in Table 2. According to the findings, air quality measured by average PM 2.5 concentration level has a considerable negative impact on house prices, in line with earlier research. However, the effect of average PM 2.5 concentration on house prices varies between 0.1 and 0.2 percent. To verify the reasonableness and robustness of the air quality indicator, we replace the 60 days with other periods before the transaction to examine the effect of changing the time period on the results.

Table 2: Regression Results of ln (price) on Number of Unhealthy Days in 60 Days

	Dependent variable:			
	log(price)			
	(1)	(2)	(3)	(4)
unhealthy60	-0.001^{***}	-0.001^{***}	-0.002^{***}	-0.002^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
square		-0.001^{***}	-0.002^{***}	-0.002^{***}
		(0.0001)	(0.00005)	(0.00004)
livingRoom		0.008^{***}	0.018^{***}	0.019^{***}
		(0.002)	(0.002)	(0.001)
drawingRoom		-0.002	0.032^{***}	0.058^{***}
		(0.002)	(0.002)	(0.002)
kitchen		0.053^{***}	0.066^{***}	0.075^{***}
		(0.011)	(0.009)	(0.008)
bathRoom		0.095^{***}	0.083^{***}	0.078^{***}
		(0.003)	(0.003)	(0.002)
floor		-0.004^{***}	-0.001^{***}	-0.001^{***}
		(0.0002)	(0.0002)	(0.0001)
constructionTime		-0.008^{***}	-0.002^{***}	-0.002^{***}
		(0.0001)	(0.0001)	(0.0001)
elevator1		0.126^{***}	0.065^{***}	0.078^{***}
		(0.003)	(0.003)	(0.002)
fiveYearsProperty1		-0.074^{***}	-0.086^{***}	-0.020^{***}
		(0.002)	(0.002)	(0.001)
subway1		0.164^{***}	0.102^{***}	0.101^{***}
		(0.002)	(0.002)	(0.001)
district2			-0.424^{***}	-0.433^{***}
			(0.004)	(0.003)

Cont. Table 2: Regression Results of ln (price) on Number of Unhealthy Days in 60 Days

	Dependent variable:			
	log(price)			
	(1)	(2)	(3)	(4)
district4			-0.653^{***}	-0.657^{***}
			(0.005)	(0.004)
district7			-0.322^{***}	-0.329^{***}
			(0.003)	(0.003)
district8			-0.073^{***}	-0.067^{***}
			(0.004)	(0.003)
district9			-0.470^{***}	-0.469^{***}
			(0.005)	(0.004)
district10			0.117^{***}	0.127^{***}
			(0.004)	(0.003)
Year2014				-0.033^{***}
				(0.003)
Year2015				0.021^{***}
				(0.002)
Year2016				0.299^{***}
				(0.002)
Year2017				0.618^{***}
				(0.004)
Constant	10.747^{***}	26.016^{***}	15.692^{***}	15.479^{***}
	(0.002)	(0.275)	(0.241)	(0.201)
Observations	179,151	168,230	168,230	168,230
R^2	0.001	0.092	0.346	0.546
Adjusted R^2	0.001	0.092	0.346	0.546
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3: Regression Results of ln (price) on ln (PM 2.5)

	Dependent variable:			
	log(price)			
	(1)	(2)	(3)	(4)
ln_PM 2.5	-0.013^{***}	-0.019^{***}	-0.014^{***}	-0.050^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
House Characteristics	NO	YES	YES	YES
District Characteristics	NO	NO	YES	YES
Year Fixed Effects	NO	NO	NO	YES
Observations	179,151	168,230	168,230	168,230
R^2	0.0001	0.091	0.345	0.547
Adjusted R^2	0.0001	0.091	0.345	0.547
Residual Std. Error	0.396 (df = 179149)	0.377 (df = 168218)	0.320 (df = 168212)	0.266 (df = 168208)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

IV.2 Sensitivity Tests

To test the result sensitivity, we do some specification test to show the robustness of conclusion. One concern is that manufactories are more likely to located in the area with lower housing price due to the cost of land, thus leading to poor air quality of that area. Such worry could be solved by 2SLS model. Usually, pollutants tend to pile up in calm conditions, when wind speeds are not more than about 10kmph. Speeds of 15kmph or more favor dispersal of pollutants, which, literally, clears the air. We find that higher wind speed can contribute to better air quality but has no correlation with housing price. Therefore, we use the average wind speed in 60 days before final transaction as instrumental variable. Table 4 shows the result that there is only a slightly decrease in the coefficient on ln_PM2.5_hat compared to the estimate one obtain with hedonic housing price regression in the previous part; all the new estimates are statistically same as the previous estimates. The finding reveals that although housing price may affect the air quality, such causality is relatively too low to hurt the robustness of our conclusion.

Table 4: 2SLS Regression Results

	(1)	(2)
	2SLS 1st stage	2SLS 2st stage
Dependent variable	log(PM 2.5)	log(price)
ln_PM 2.5		-0.011***
		(0.001)
ln_wind speed	-0.542***	
	(0.000)	
House Characteristics	YES	YES
District Characteristics	YES	YES
Year Fixed Effects	YES	YES
F test on Ivs		12.13
Hansen J stat. /P-value		0.30/0.86
Observations	168230	168230
Adjusted R^2	0.192	0.565

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Another worry could be that the way we use only the number of unhealthy days (the average level of PM 2.5 concentration $>$ 100) to represent the pollution impression of buyers on the house may be biased since people's impression on air quality is more "fine-grained" which can hardly be quantified by the binarized "healthy" or "unhealthy" label. So, we reclassify into 6 levels (good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, hazardous) of air quality and count the number of days. Additionally, we replaced the span of 60 days with other time periods before the transaction, and examined the impact of changing the time span on the results. Columns (1) to (4) in Table 5 respectively show the impact of changes in air quality level on the 7, 30, 120, and 365 days before transaction. From 30 days before the transaction, air quality began to significantly affect house prices. For each day that hazardous level air quality was increased, the average house price dropped by 0.1% to 0.3%. The results show that the pollution from one month to one year before the transaction will significantly reduce the transaction price of the house, but the effect within 30 days is not obvious.

Table 5: Regression on different time period selection and reclassification of the air quality

	Dependent Variable:			
	log(price)			
	(1) 7 days before	(2) 30 days before	(3) 120 days before	(4) 365 days before
good days	-0.001	0.001*	0.002***	0.002***
	(0.360)	(0.095)	(0.000)	(0.000)
moderate days	0.001	0.002	0.000***	0.001***
	(0.934)	(0.168)	(0.000)	(0.000)
unhealthy for sensitive groups day	-0.001	-0.000**	-0.001***	-0.001***
	(0.660)	(0.043)	(0.000)	(0.000)
unhealthy days	-0.002	-0.001***	-0.002***	-0.001***
	(0.273)	(0.000)	(0.000)	(0.000)
very unhealthy days	-0.003	-0.002*	-0.004***	-0.004***
	(0.233)	(0.078)	(0.000)	(0.000)
hazardous days	-0.001	-0.000**	-0.003***	-0.003***
	(0.715)	(0.027)	(0.000)	(0.000)
House Characteristics	*YES*	*YES*	*YES*	*YES*
District Characteristics	*YES*	*YES*	*YES*	*YES*
Year Fixed Effects	*YES*	*YES*	*YES*	*YES*

Note: *p<0.1; **p<0.05; ***p<0.01

Finally, one might be concerned that higher house price implies wealthier households who are willing to pay more for better air quality. Based on the total house transaction price and the average house price per square meter, we select sub-samples in the upper and lower 25% quantile of the data, and compare the impact of air quality on house prices in different sub-samples. Columns (1) to (4) in Table 6 show that regardless of whether the sample is divided according to the total price or the average price, in the sub-sample of the lower 25% quantile, the coefficient of influence of air quality on house price is smaller and the significance is also lower compared with the results of the upper 25% quantile. Good air quality itself is luxury and therefore is favored more by wealthier families.

Table 6: Regression on upper and lower 25% quantile of average housing price and total price

	total price		average price	
	(1)	(2)	(3)	(4)
	upper 25%	lower 25%	upper 25%	lower 25%
unhealthy days	-0.003***	-0.002**	-0.002***	0.001
	(0.000)	(0.023)	(0.000)	(0.372)
House Characteristics	*YES*	*YES*	*YES*	*YES*
District Characteristics	*YES*	*YES*	*YES*	*YES*
Year Fixed Effects	*YES*	*YES*	*YES*	*YES*
Observations	42058	42058	42058	42058
Adjusted R^2	0.65	0.462	0.594	0.532

Note: *p<0.1; **p<0.05; ***p<0.01

V Conclusion

This paper provides another insight into the value of better air quality. Cleaner air would not only benefit people's health but also increase homeowners' wealth. By comparing houses in Beijing urban area associated with a different number of unhealthy days in 60 days before the house was traded, we find that people place a higher value on better air quality. People are willing to pay 0.2 percent more for houses associated with one more healthy day. Our results are robust to the sensitivity tests and omitted variable bias. Furthermore, our results show that there is a disparity between higher- and lower-income households' preferences. Wealthier households are willing to pay more for better air quality.

There are several shortcomings of this study. We study how Beijing urban residents value air quality, and this may not represent the preferences of residents in other places. Nevertheless, this study could help policymakers to evaluate the air pollution policy in Beijing. For example, the central government has moved several factories in Beijing to the adjacent province of Hebei to improve air quality. The most famous one among those relocated is the

Shougang Group which is one of the largest steel manufacturers in China. The policymaker could count the number of healthy days after the relocation of these factories and estimate the financial benefits to people in Beijing.

To sum up, the value of better air quality can be inferred from housing prices. This study brings us closer to understanding the effect of various environmental policies. However, policymakers also need a better understanding of what causes air pollution to improve the effectiveness of these policies.

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