

# 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 China's worst affected areas by air pollution. 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 the housing prices will decrease by 0.1 to 0.3 percent for one more unhealthy day before the transaction. This result is robust to sensitivity checks and omitted variables bias. Furthermore, we find 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 is an issue that not only affects 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 overemphasis on economic growth, air pollution has become a major environmental problem in China. Figure 1 illustrates the relationship between GDP per capita and the PM 2.5 from 1990 to 2016. Air quality in China has rapidly deteriorated as the country's economy has grown.

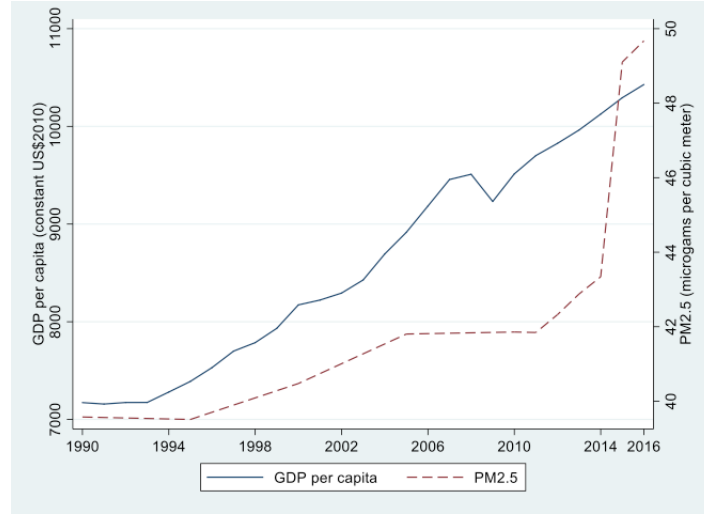


FIGURE 1: China's GDP per capita and PM 2.5 from 1990 to 2016

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 on the median housing price of each American county. They found that decreasing total suspended particulates by one microgram per cubic meter raises 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 examined local-level real estate markets. Anderson and Crocker [AJC71] quantified the residential value of the property based on 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, because it takes time for buyers to move from viewing to purchasing a home, focusing solely on the impact of pollution levels 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. To begin, we match each house to the nearest air pollution monitoring centers in order to obtain accurate PM 2.5, and then we regress house price on PM 2.5 with several control variables. Our result indicates that the housing price will decrease by 0.16 percent for one more unhealthy day 60 days before the transaction. This finding elucidates how people value better air quality, which helps policymakers evaluate environmental policies. In addition, we investigate the wealth effect on willingness to pay for clean air. According to the findings, wealthier households are willing to pay more for better air quality. Overall, our findings show that improved air quality not only benefits 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:

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

where the price is the housing price per square meter of each observation.  $N$  is the number of unhealthy days 60 days before the transaction.  $H$  is the house characteristics.  $D$  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 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 PM 2.5 for every community. Therefore, we can control the taste heterogeneity and avoid underestimating the variation in individual preferences. Secondly, We take the buyer’s decision-making process into account by using average air quality 60 days before the transaction as a proxy. As a result, 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 homes. Finally, as the capital city, Beijing prioritizes air quality improvement and regulation, 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, there is a significant difference in air quality between the north and south of Beijing. The heavy industries of Beijing are concentrated in the south, producing a large amount of pollution, 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. In general, PM 2.5 levels are 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.

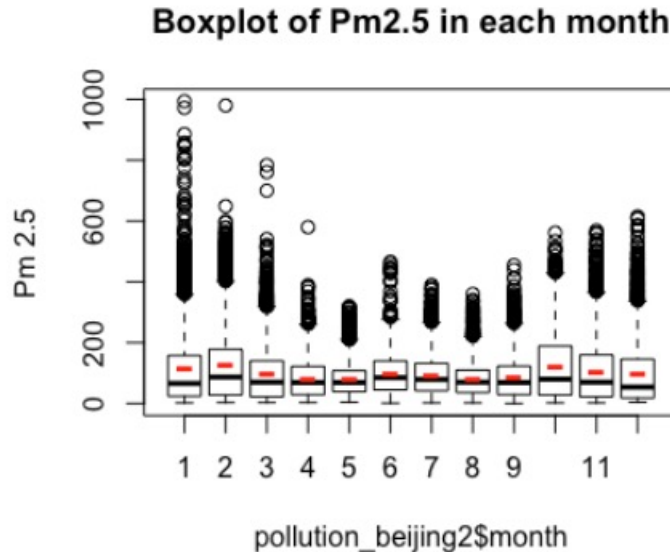


FIGURE 2: Boxplot of monthly trend of PM 2.5 in Beijing from 2013 to 2017

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.

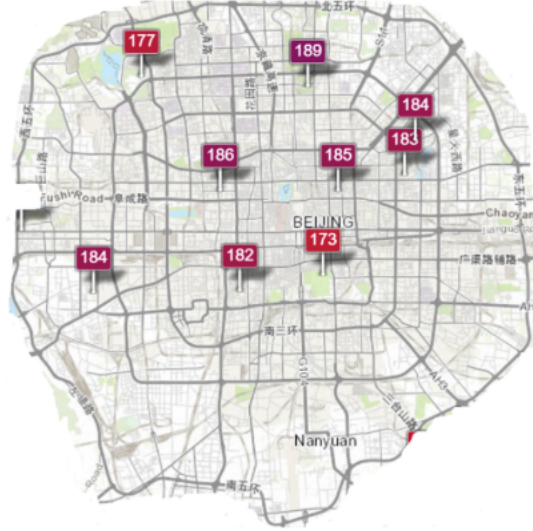


FIGURE 3: Locations of 9 Air Pollution Monitoring Sites in Beijing Urban Area

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].

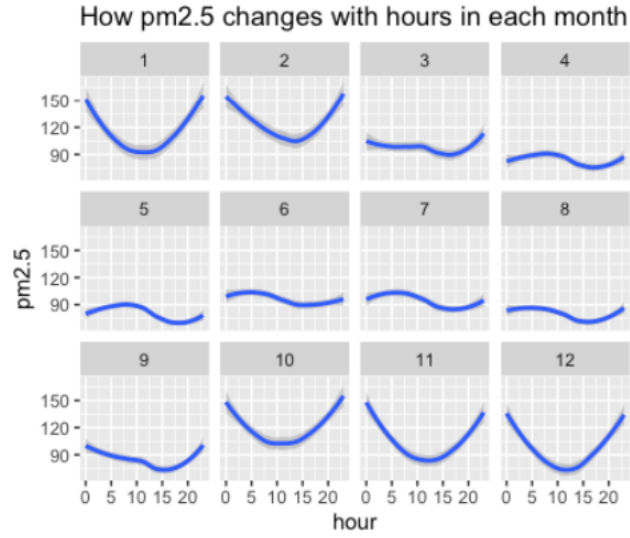


FIGURE 4: Hourly PM 2.5 Changes in Each Month

### 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.

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

## 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 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  $\ln(\text{price})$  on Number of Unhealthy Days in 60 Days

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

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

	<i>Dependent variable:</i>			
	log(price)			
	(1)	(2)	(3)	(4)
district4			−0.653*** (0.005)	−0.657*** (0.004)
district7			−0.322*** (0.003)	−0.329*** (0.003)
district8			−0.073*** (0.004)	−0.067*** (0.003)
district9			−0.470*** (0.005)	−0.469*** (0.004)
district10			0.117*** (0.004)	0.127*** (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*** (0.002)	26.016*** (0.275)	15.692*** (0.241)	15.479*** (0.201)
Observations	179,151	168,230	168,230	168,230
R <sup>2</sup>	0.001	0.092	0.346	0.546
Adjusted R <sup>2</sup>	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)

	<i>Dependent variable:</i>			
	(1)	(2)	(3)	(4)
ln_PM 2.5	−0.013*** (0.003)	−0.019*** (0.003)	−0.014*** (0.003)	−0.050*** (0.003)
House Characteristics	<i>NO</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
District Characteristics	<i>NO</i>	<i>NO</i>	<i>YES</i>	<i>YES</i>
Year Fixed Effects	<i>NO</i>	<i>NO</i>	<i>NO</i>	<i>YES</i>
Observations	179,151	168,230	168,230	168,230
R <sup>2</sup>	0.0001	0.091	0.345	0.547
Adjusted R <sup>2</sup>	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

We run several specification tests to demonstrate the robustness of our findings. One concern is that the way we classify unhealthy days (the average level of PM 2.5 concentration  $> 100$ ) may not accurately represent buyers' perceptions of pollution. Since people's perceptions of air quality are more nuanced, it is inaccurate to quantify air quality using the binary "healthy" or "unhealthy" labels. Therefore, we reclassify air quality into six categories (good, moderate, unhealthy for sensitive groups, unhealthy, very unhealthy, hazardous) and count the number of days in each category. Additionally, we replace the 60-day period with other time periods preceding the transaction and investigate the effect of changing the time span on the results. Columns (1) to (4) in Table 5 show the effects of changes in air quality levels on the 7, 30, 120, and 365 days before trading, respectively. Within a 30-day period, the effect is not significant; however, air quality significantly affects home prices over a more extended period of time. An additional day in unhealthy conditions will decrease the average home price by 0.1% to 0.3%. When air pollution becomes more severe, home prices will drop even more.

Table 4: Regression on different time period selection and reclassification of the air quality

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

Another worry is that, due to land costs, factories are more likely to locate in areas with lower housing prices, resulting in poor air quality. To verify whether there is a casual relationship, we apply the 2SLS model. Typically, pollutants accumulate in calm conditions when wind speeds are less than 10 mph; wind speeds above 15 mph facilitate pollutant dispersion, thus cleaning the air. Since higher wind speeds improve air quality but have no direct effect on housing prices, we use the average wind speed 60 days before the final transaction as an instrumental variable. Table 4 shows that the coefficient on  $\ln\_PM2.5\_hat$  is slightly lower than the estimates obtained in the previous section using the hedonic housing price regression; all new estimates are statistically identical to the earlier estimates. This finding suggests that, while housing prices may affect air quality, the causal relationship is too weak to harm the robustness of our conclusions.

Table 5: 2SLS Regression Results

	(1)	(2)
	2SLS 1st stage	2SLS 2st stage
<i>Dependent variable</i>	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 <sup>2</sup>	0.192	0.565

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

### IV.3 Income Effect

We are interested in what type of goods clean air is and whether or not wealthy households are willing to pay more for better air quality. Based on the total house transaction price and the average price per square meter, we select subsamples in the upper and lower 25% quantile of the data and compare the impact of air quality on house prices in different subsamples. Columns (1) to (4) of Table 6 show that the coefficient of the effect of air quality on house prices is smaller and less significant in the subsample in the lower 25% compared to the

results in the upper 25%, regardless of whether the sample is divided by total price or by average price. In conclusion, clean air is a luxury good and therefore more preferred by wealthier households.

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*** (0.000)	-0.002** (0.023)	-0.002*** (0.000)	0.001 (0.372)
House Characteristics	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
District Characteristics	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
Year Fixed Effects	<i>YES</i>	<i>YES</i>	<i>YES</i>	<i>YES</i>
Observations	42058	42058	42058	42058
Adjusted R <sup>2</sup>	0.65	0.462	0.594	0.532

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

## V Conclusion

The main goal of this study is to investigate the value of better air quality. One of the most significant findings from this study is that housing prices will decrease by 0.1 to 0.3 percent for one more unhealthy day before the transaction. This result is robust to the sensitivity tests and omitted variable bias. Furthermore, we examined the income effect of clean air. Our results show a disparity between higher and lower-income households' preferences: wealthier families are willing to pay more for better air quality. These results suggest that cleaner air would not only benefit people's health but also increase homeowners' wealth.

The current findings add to a growing body of literature on air quality premium. Our results agree with many research conducted at different times and locations. One of the most significant contributions of this research is to use the number of unhealthy days before the transaction as a proxy for air pollution to consider the buyer's decision-making process. The data and regression we use are comparable to Qin et al. [QWY19], resulting in a significant and robust negative relationship. In addition, this study could help policymakers evaluate Beijing's air pollution policy. For example, the Chinese government has moved several factories in Beijing to the adjacent province of Hebei to improve air quality, including Shougang

Group, one of China's largest steel manufacturers. The policymaker could count the number of healthy days after the relocation of these factories and estimate the financial benefits to Beijing homeowners.

The generalisability of these results is subject to certain limitations. For instance, we only study how Beijing urban residents value air quality, which may not represent residents' preferences in other places. In conclusion, This study brings us closer to understanding the effect of various environmental policies. More research is required to determine the factors that impact air pollution to improve the effectiveness of these policies

## References

- [AJC71] Robert J Anderson Jr and Thomas D Crocker. Air pollution and residential property values. *Urban Studies*, 8(3):171–180, 1971.
- [CG05] Kenneth Y Chay and Michael Greenstone. Does air quality matter? evidence from the housing market. *Journal of political Economy*, 113(2):376–424, 2005.
- [CJZ07] Eugene K Cairncross, Juanette John, and Mark Zunckel. A novel air pollution index based on the relative risk of daily mortality associated with short-term exposure to common air pollutants. *Atmospheric environment*, 41(38):8442–8454, 2007.
- [NPA21] Yevgen Nazarenko, Devendra Pal, and Parisa A Ariya. Air quality standards for the concentration of particulate matter 2.5, global descriptive analysis. *Bulletin of the World Health Organization*, 99(2):125, 2021.
- [QWY19] Yu Qin, Jing Wu, and Jubo Yan. Negotiating housing deal on a polluted day: Consequences and possible explanations. *Journal of Environmental Economics and Management*, 94:161–187, 2019.
- [SH95] V Kerry Smith and Ju-Chin Huang. Can markets value air quality? a meta-analysis of hedonic property value models. *Journal of political economy*, 103(1):209–227, 1995.
- [TN21] Minmeng Tang and Deb Niemeier. How does air pollution influence housing prices in the bay area? *International journal of environmental research and public health*, 18(22):12195, 2021.