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Air Pollution and the Effects on House Prices: A Push for Sustainability

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ABSTRACT
Environmental sustainability has become an important issue of concern throughout many countries. Among the many sources of concern include air pollution, the effects of which are often capitalized into house prices. In this article, we focus on air pollution in the city of Changsha, China, and the impacts of new pollution regulations on the relationship between pollution exposure and house sales prices. We use the Air Quality Index (*Aqi*) data from 10 air quality monitoring stations in Changsha to interpolate a previous 12-month average *Aqi* value for each dwelling unit in the city, based on geographical location. Controlling for important house characteristics such as the living area and the distance to the nearest subway stations, we use the Blue Sky Protection Campaign action plan (BSPC) as the quasi-natural experiment to identify the causal effect of air pollution on house prices. We find dwelling units that were previously in relatively higher-polluted neighborhoods saw their values increase by about 2% after the pollution regulation was implemented, which is statistically significant. This implies China could achieve greater housing wealth for its homeowners by implementing further pollution restrictions, both in Changsha and perhaps also in other parts of the country. Other Asian countries could potentially learn from the results of this analysis.

KEYWORDS
Sustainability; air pollution; China; house prices

1. Introduction

Air pollution is one of the major problems in the rapid urbanization and industrialization process in developing countries, which has a significant positive correlation with heart disease, respiratory disease, and mortality (Chay & Greenstone, 2005; Deryugina et al., 2019; Greenstone & Hanna, 2014). Poor air quality also has a significant negative impact on medical expenditure, labor supply and participation, and residents' income (Hanna & Oliva, 2015; Isen et al., 2017), with enormous health and socioeconomic costs. To mitigate the detrimental effects of pollution emissions on public health and climate change, governments worldwide have been implementing air pollution regulations. Although environmental regulation may lead to improved air quality, it may also have a temporary negative impact on local economic development. It is essential to assess how much

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value individuals attach to improving air quality, that is, residents' willingness to pay (WTP) for clean air, to strike a balance between economic growth and protection of the environment.

These problems have been addressed extensively in the real estate economics literature because these types of externalities often become capitalized into housing prices. However, the empirical evidence on accurate estimates of WTP for improved air quality is limited, especially in the Chinese context. Earlier studies primarily emphasized the hedonic model developed by Rosen (1974), which assumes that housing prices are influenced by their features, such as air quality, and the marginal price of a house characteristic is given as the regression coefficient for that specific characteristic. Although better air quality may be associated with higher house prices, it may also be possible that polluting firms might be encouraged to locate near houses of lower value, leading to biased estimates (Kim et al., 2003).

More recently, real estate studies have taken environmental regulation as a quasi-experiment and incorporated hedonic models to determine the causal relationships between disamenities and house prices. See Diao et al. (2016) for an example of noise pollution in Singapore and Amini et al. (2022) for an example of air pollution in Iran. Such an identification strategy is similar to how we test the hypothesis that air quality impacts house prices in this paper. Government regulations and policies can have significant impacts on environmental quality (Jiang et al., 2021; Zhang & Wu, 2018). The residents might be willing to pay more for houses in locations with better air quality than those with worse air quality. Air pollution might be reflected in lower house values. However, the pollution "discount" might not be as high after a pollution regulation as before the regulation is implemented. Therefore, this article uses the regulations of the "Three Year Action Plan to Win the Blue Sky Protection Campaign" (hereinafter referred to as the "Blue Sky Protection Campaign" and abbreviated as BSPC) promoted by the central government of China in 2018 as a quasi-natural experiment to estimate the impact of air quality on housing prices. This approach overcomes the potential endogeneity in the hedonic price model. First, we interpolate pollution levels from 10 fixed air quality monitoring stations to each dwelling unit location in the city of Changsha and aggregate the hourly data up to monthly to derive estimates of average annual pollution exposure for each dwelling unit at the month of sale within Changsha city. We find that after the BSPC regulations are implemented, houses are sold for more than they would have before the regulations. The magnitude of this effect is about 2%, depending on the model specification, and is statistically significant.

There are several innovations in our article. First, the relevant research on Chinese WTP for clean air is relatively limited. Most of those papers use provincial or city-level panel data for research (Wang et al., 2022; Wang & Lee, 2022), which cannot reflect the heterogeneity of housing prices and air quality in different regions within the cities and the dynamic responses of households. For instance, households may move to areas with better air quality in the same city, which could result in biased estimates of aggregated data at the city level. We use an individual dwelling unit dataset of Changsha city in China to estimate the residents' WTP, which can help us to overcome the potential limitations of macro (i.e., city or province) level data. Second, considering the latent endogeneity, we use a hedonic house price model, together with difference-in-differences estimation techniques, to derive causal estimates of this relationship before and after the enforcement of BSPC regulations. This estimation strategy enables us to answer the question of how air pollution exposure impacts house prices. Our primary focus is on overall pollution emissions, i.e. the air quality index (*Aqi*). However, we also separately consider emissions of the pollutants PM2.5 and SO_2, which were the main targets of the regulations under consideration.

Another innovation of our approach is the way in which we control for the property time on the market (TOM). While houses with longer TOM might be expected to sell for less, it is also the case that lower-priced houses should sell more quickly (i.e. they would have a shorter TOM). Regression results may be biased and inconsistent without recognizing and controlling for this type of simultaneity. We build on existing approaches for addressing this TOM simultaneity, such as Turnbull and Dombrow (2006), with a three-stage least squares (3SLS) approach. The results from the 3SLS approach show that our findings are robust to the endogeneity issue.

The remainder of this paper proceeds as follows. First, we review the literature on the impact of air quality on housing prices. Then, we describe our estimation strategies, model, and data. The following section of the paper presents our empirical findings on the effects of overall pollution levels on house prices and some robustness checks. Finally, the paper concludes with a summary of findings and suggestions for future research.

2. Literature Review

Air quality is a crucial factor affecting people's quality of life and well-being. Poor air quality negatively affects human health and significantly impacts the economy, such as productivity, earnings, and employment, and is often reflected in housing prices (Fan et al., 2023; Hanna & Oliva, 2015; He et al., 2019; Jiang et al., 2020). Prospective buyers may consider the health risks associated with living in a polluted area, and this is expected to reduce demand for properties exposed to more pollution. Ultimately, pollution may lead to lower WTP for this type of housing nearby and, in turn, reduced dwelling prices.

Many earlier studies consider air quality as one of the housing attributes and use the traditional hedonic and/or spatial hedonic pricing methods to empirically estimate the effects of air quality on housing prices (Kim et al., 2003; Smith & Huang, 1995). More recent literature has made advances to overcome endogeneity bias by relying on natural or quasi-natural experiments of external factor changes, such as the closure of a nearby factory (Mei et al., 2021) or implementing an environmental policy (Chay & Greenstone, 2005). Most of these studies have identified adverse impacts of air pollution on housing prices.

But research on the relationship between air pollution and housing prices in China has produced mixed findings, with some studies having found a negative effect (Chen et al., 2018; Hao & Zheng, 2017; He & Collins, 2020; Li et al., 2022; Liu et al., 2018), and others having uncovered a positive effect (Wang & Cai, 2021; Zou et al., 2022). The impact of air pollution on housing prices depends on the level of economic development, the city's size, the residents' awareness, and their income (Wang et al., 2022).

Policy interventions aimed at reducing air pollution may present opportunities to increase housing values and improve living conditions for communities most affected by poor air quality. Feng et al. (2019) examined the effectiveness of the APPCAP in China and found a significant improvement in overall air quality (also see Fan et al., 2023). However, this policy has different effects on different pollutants, cities, and time periods (Cai et al., 2017; Li et al., 2021). Promoting technological innovation, public transportation, and industrial agglomeration can lead to positive policy effects (He et al., 2024). Based on city-level panel data, Jiang et al. (2021) examine the BSPC as a quasi-natural experiment and find that the BSPC reduces the monthly average concentration of PM2.5 and PM10 in cities.

Most of the previous studies based on Chinese data use city-level data on housing prices and PM2.5 pollutants to analyze the impact of air quality on housing prices (Chen & Chen, 2017; Chen & Jin, 2019; Zhang et al., 2021). Using a panel dataset of 280 cities from 2003 to 2018 in mainland China, Fan et al. (2023) examine the cross-city variation in the implementation timing of China's clean air policy and find that implementing the clean air policy boosts housing values by 4.4%. City-level data are the aggregated mean of household data, which may not reflect the heterogeneity of housing prices and pollution levels in different regions within the city and the dynamic responses of households. For example, households might relocate to areas that have improved air quality, and policies aimed at reducing air pollution can impact the job market and spillover to the housing market, biasing the estimates of city-level aggregate data. Our paper uses dwelling transaction-level data within Changsha city in China between 2016 and 2021. Transaction-level data helps us to explore the nexus between air quality and housing prices from a microscopic viewpoint and complements the existing city-level literature.

3. Background and Estimation Strategy

3.1 The 2018 BSPC Action Plan and Related Institutional Background

On June 27, 2018, the Chinese State Council implemented the BSPC, aiming to reduce the levels of fine particulate matter (PM2.5) and sulfur dioxide (SO_2) in the air.

BSPC is based on the Air Pollution Prevention and Control Action Plan (APPCAP) of 2013, which aims to improve air quality mainly in the Beijing-Tianjin-Hebei region (or so-called Jing-Jin-Ji region) and nearby areas. Despite the overall improvement in air quality in China due to APPCAP, challenges remain. In 2017, more than 70% of China's 338 cities did not meet air quality standards.[1] The Chang-Zhu-Tan area of Hunan Province (with Changsha as its capital) still maintains a high level of PM2.5 and experiences severe O_3 pollution (Feng et al., 2019). When compared to the APPCAP period, the BSPC places greater emphasis on air pollution sources in the heating, energy, metals and mining, and transportation sectors. Additionally, the industrial environmental protection standards and emission standards of plant productions, vehicles and ships are more strictly enforced, leading to a significant increase in environmental protection inspections and production curbs (Jiang et al., 2021).

The BSPC Action Plan outlines relevant principles, goals, tasks, and measures with a timetable and roadmap for successful implementation. The goal has been to decrease the release of significant air pollutants and greenhouse gases, resulting in a reduced density of PM2.5 and fewer days with significant pollution. According to the plan, there should be a decline of at least 15 percent in SO_2 from 2015 levels by 2020, nationwide. Moreover, cities with inadequate air quality standards ought to experience a minimum of 18 percent decrease in PM2.5 density. In addition, the cities at the prefecture level and above should reach an annual rate of 80% for days with "good" air quality, and the number of days with heavy pollution should decrease by 25% or more compared to the levels in 2015.[2]

To achieve these objectives, the State Council has encouraged officials to alter industrial structures and support environmentally friendly growth. This includes rectifying the energy structure for a better, cleaner, and more efficient energy system, enhancing green transportation, and optimizing land use systems to better control pollution. Several actions and plans have been implemented to lower pollution, coordinate prevention and control measures during severely polluted days, and enhance laws, regulations, and policies. To protect the environment, authorities have also been focusing on building infrastructure and capacities, strengthening law enforcement, and involving the community in environmental protection. Compared with the APPCAP, BSPC addresses more specific aspects of pollution and forms a joint defense mechanism as well as inter-regional joint prevention and control measures. The transition from a small alliance to a major one has improved air quality (Song et al., 2020).

As of the end of 2020, the average proportion of days in 337 cities at or above the nationwide prefecture level was 87.0%. The average fine particulate matter (PM2.5) concentration was 33 micrograms per cubic meter, and the average concentration of major pollutants decreased significantly, year after year. As a result, the overall goals and quantitative targets were surpassed.[3]

Also, in June 2018, the government of Hunan Province released the Three-Year Action Plan for Pollution Prevention and Control for Hunan Province (2018–2020) (Xiangzhengfa [2018] No. 17) was initiated in response to the BSPC policy undertaken by the central government. The plan highlights the atmospheric co-governance in the Changsha-Zhuzhou-Xiangtan region (the three cities are adjacent to each other) and strengthens three major measures (i.e. economic development mode transformation, pollution control, and ecological protection targeting significantly increasing the number of days of excellent environmental air quality in the province through three years of efforts). The plan has clear goals concerning the air quality in the province. The plan dictates that by 2018, 2019, and 2020, the province's average annual concentration of PM 2.5 should decrease to no more than 44 $\mu g/m^3$, 42 $\mu g/m^3$, and 40 $\mu g/m^3$, respectively. Specific to Changsha city, by 2020, the average annual concentration of PM 2.5 in Changsha should decrease to 44 $\mu g/m^3$, the SO_2 should reduce by over 9% compared to 2017, the rate of urban ambient air quality should be excellent over 80% of the time, and the total number of heavily polluted days should not exceed 15.

After 3 years of implementation in BSPC, the number of days of excellent air quality in Changsha had significantly increased. As of August 31, 2020, the city's air quality had been excellent 90.2% of the time. The average annual concentration of PM 2.5 is 35 $\mu g/m^3$, a year-on-year decrease of 18.6%.[4]

3.2. Empirical Strategy

Our main hypothesis is that air pollution reduces the value of houses, and implementing BSPC can mitigate the negative effects of air pollution on housing prices. We begin by estimating the hedonic model to examine the impact of air quality on housing prices.

$$HP_{ijt} = \alpha_0 + \alpha_1 \cdot Aqi_{it} + \alpha_2 \cdot \mathbf{X}_\mathrm{i} + d_\mathrm{j} + \epsilon_\mathrm{t} + \varepsilon_{it}, \tag{1}$$

where HP_{ijt} is the log of the housing price of dwelling unit *i* in district *j* at time *t*;[5] Aqi_i is the log of the average *Aqi* of 12 months prior to the transaction month at the geographic location of dwelling unit *i* that sold at time *t*; $\boldsymbol{X_i}$ is a vector of covariates representing the characteristics of dwelling unit *i*, including the property area, the age of the property at the time of the transaction, the amount of time the property is on the market (TOM), the distance to the nearest subway station entrance, the district's Gross Domestic Product (GDP), and the district population, as in Zheng et al. (2019). We also include district fixed effects (d_j), which are included to control for unobservable factors that are constant over time but vary across different municipal districts governed by Changsha; ϵ_t includes year-fixed effects, which are included to control for common factors; and ε_{it} is the error term.

Our estimation strategy is based on the notion that poor air quality can have a negative impact on the prices of housing units. The higher the *Aqi* in the area where the dwelling unit is located, the lower the housing prices. Thus, α_1 is expected to be negative. But, the impact of air quality on housing prices is likely influenced by the behavior or actions of consumers or firms in the area where the dwelling unit is located. Areas with higher housing prices may attract more people with automobiles due to the possible higher quality of living. If more residents, cars, or retail activities are in the developed areas with higher housing prices, there is likely a corresponding increase in pollution levels due to the activities of the more densely populated activities. Although some of the regression variables, such as the shortest distance to the subway entrance, the district GDP, the district population, and the lagged *Aqi* estimate, might help to mitigate the endogeneity problem to some extent, we use the BSPC Policy as a quasi-natural experiment to address the possible endogeneity issues further. This identification strategy leads to the following model:

$$HP_{ijt} = \beta_0 + \beta_1 \cdot Aqi_{it} + \beta_2 \cdot BSPC_\mathrm{t} + \beta_3 \cdot Aqi_{it} \times BSPC_\mathrm{t} + \gamma \cdot \mathrm{X_i} + d_\mathrm{j} + \epsilon_\mathrm{t} + \varepsilon_{it} \tag{2}$$

where $BSPC_t$ is a dummy variable equal to one for all months after June 27$^{\text{th}}$, 2018, and zero for all months prior to that date. This indicator variable proxies for the BSPC policy. The other regressors are identical to those used in Equation (1).

Our estimation strategy is a variant of the standard differences-in-differences (DID) approach with continuous treatment (i.e. Aqi_{it}) and compares the relative change in housing prices between different air quality locations in the pre-adoption and post-adoption periods. The difference between our approach and a standard DID method is that we use a continuous proxy of our treatment variable, allowing us to capture more variability in the data.[6] Here, we hypothesize that implementing the BSPC policy can help improve the air quality and thus mitigate the negative impact of air pollution on housing prices. This DID strategy allows us to compare houses in locations with considerable levels of air pollution with houses in locations with less pollution. Our coefficient of interest, β_3, estimates the effect of the BSPC on air quality impacts on dwelling unit housing prices and is expected to be positive. Specifically, a positive estimate of β_3 indicates that, after the adoption of BSPC, the price of houses in locations with initially relatively severe air pollution increased more than house prices in areas with relatively light air pollution.

To test the robustness of the hypothesis, we also substitute the continuous Aqi_{it} with a dummy variable ($D_{50,i}$) that indicates whether the estimated Aqi_{it} at a specific dwelling unit location is higher than the mean estimated Aqi_{it} value in each month. This can be expressed as:

$$HP_{ijt} = \beta_0 + \beta_1 BSPC_t + \beta_2 D_{50,i} + \beta_3 \cdot \mathrm{D}_{50,\mathrm{i}} \times BSPC_{\mathrm{t}} + \gamma \cdot \mathrm{X}_{\mathrm{i}} + d_{\mathrm{j}} + \epsilon_{\mathrm{t}} + \varepsilon_{it} \tag{3}$$

where $D_{50,i}$ is a dummy variable that equals one if the dwelling unit i is in an area with an estimated 12-month prior *Aqi* higher than the mean estimated *Aqi* in the transaction month, and it equals zero otherwise. The coefficient of interest, β_3, is an estimate of the role played by the BSPC for the air quality impacts on dwelling unit housing prices in relatively heavily polluted areas. Our hypothesis is supported if β_3 is significantly positive.

Equations (2) and (3) examine the average effect of the BSPC policy on housing prices in areas experiencing improved air quality. The estimation requires that no other factor or policy significantly impacted Changsha's air quality before the BSPC implementation. To further explore the validity of this assumption, we estimate a fully flexible equation that takes the following form:

$$HP_{ijt} = \beta_0 + \beta_1 \cdot \mathrm{D}_{50,\mathrm{i}} + \sum_{\mathrm{p}=-7}^{12} \alpha_{\mathrm{p}} \cdot \mathrm{D}_{50,\mathrm{i}} \times \mathrm{I}_{\mathrm{p}} + \gamma \cdot \mathrm{X}_{\mathrm{i}} + d_{\mathrm{j}} + \epsilon_{\mathrm{t}} + \varepsilon_{it} \tag{4}$$

where all variables are defined as in Equation (3). The only difference from Equation (3) is that in Equation (4), rather than interacting $D_{50,i}$ with a post-BSPC adoption indicator variable, we interact it with time fixed effects, I_p. The estimated vector of α_p proxies the association between air quality and the outcomes of interest in each time period. If no other factor improved the air quality significantly in Changsha before BSPC, we would expect the estimated α_p to be constant over time for the periods before BSPC was adopted.

Next, we explore alternative specifications to check the robustness of our results. Specifically, we use the log of the *Aqi* averaged throughout the pre-treatment period as the proxy for the air quality. Unlike the time-varying air quality proxy we used in Equations (1) and (2), this variable is a time-invariant proxy for *Aqi*. This specification allows us to compare the relative change in housing prices between the locations with different air quality in the pre- and post-adoption periods. We also use PM2.5 and SO_2 as the air pollution proxies since they are the main target pollutants for the BSPC. We adjust the time horizon by averaging the air quality index over 3, 6, and 9 months before the transaction month. For a further robustness check, we add the number of nearby restaurants, a proxy for "point of interest" (POI), to our model to control for the economic development level. We also control for the possible simultaneity of *TOM* and price. Finally, we tested the policy anticipation effect and assessed the role played by the Covid-19 pandemic.

3.3 Data and Variables

Changsha, the capital city of Hunan province in China, governs over 6 municipal districts (Furong, Tianxin, Yuhua, Kaifu, Yuelu, Wangcheng), one county (Changsha County), and two county-level cities (Liuyang and Ningxiang). As of the end of 2021, the city had a total population of 10.24 million, with a density of around 867 individuals per square kilometer. Changsha's nominal GDP for 2021 was 1327.07 billion yuan (equivalent to about 205.7 billion US dollars), ranking 15th among Chinese cities at the prefecture level and above.[7]

We have obtained the transaction data of previously owned dwelling units in Changsha from January 2016 to December 2021, from the database CnOpenData. The data includes information such as the dwelling unit transaction price, area, residential complex, location, transaction date, listing date, and other variables. We obtain each dwelling unit's GCJ-02 coordinate system longitude and latitude based on its street address.[8]

The air pollution data comes from the China National Environmental Monitoring Centre (CNEMC), an institution under the Ministry of Ecology and Environment. It provides hourly *Aqi* updates based on its assessment of air pollution levels. The overall average value of pollutant concentration in the built-up areas of the city is proxied by the final *Aqi*, which is calculated from the arithmetic mean value of all air pollutants (e.g. SO_2, PM2.5) concentration of monitoring stations in the city, based on the Environmental Air Quality Standard (GB3095-2012).[9] As the *Aqi* increases, the air quality decreases. There are 10 monitoring stations in Changsha.

We use the hourly *Aqi* data reported by the 10 monitoring stations, calculate daily averages from the hourly data, and the monthly averages based on the daily data for each station. Figure 1 shows the monthly mean levels of PM2.5, PM10, SO_2, NO_2, $O_{3,}$ and CO from station 2, ranging from January 2016 to December 2021.[10] After the implementation of the BSPC (as shown by the red line), the level of SO_2 decrease significantly, fulfilling one of the policy goals of the BSPC agenda. Comparing the 2016 and 2021 data, the PM2.5, PM10, and NO_2 concentrations decrease slightly at the end of 2021. The pattern of O_3 and CO concentrations displayed on the graph is unclear.

Considering the spatial autocorrelation of air quality, we then calculate the distance between each pollution station and every dwelling unit using their latitude/longitude coordinates. We use the Inverse Distance Weighting (IDW) interpolation approach as in Feng et al. (2023) to compute the interpolated weighted monthly average of the 10 monitoring stations' pollution exposure for each dwelling unit (see Equation (6)).

$$Interpolated\ \ Aqi_{it} = \sum\nolimits_{m=1}^{10} \lambda_{im} \times Aqi_{mt}; \lambda_{ij} = \frac{1/d_{im}}{\sum\nolimits_{m=1}^{10} \frac{1}{d_{im}}} \tag{6}$$

where d_{im} is the distance between dwelling unit i and monitoring station m, Aqi_{mt} is the monthly air quality index of monitoring station m at time t, Aqi_{it} is the interpolated monthly air quality of dwelling unit i at time t calculated using the IDW interpolation approach.

Considering that dwelling purchase is a long-term decision and different climates in different months of the year can be associated with various pollution exposure levels for each dwelling, we construct a pre-12-month moving average *Aqi* variables by averaging the monthly pollution exposure calculated based on Equation (6) for 12 months before each property's transaction month. We use this estimate as a proxy for the air quality index at the sale date. As a concrete example, suppose that the date of sale for a house

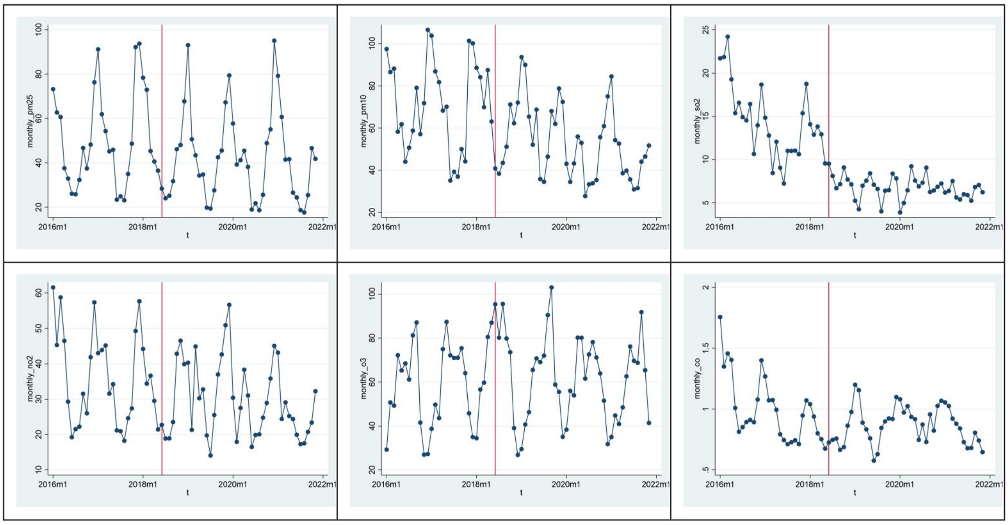


Figure 1. The monthly trend of six major pollutant concentrations at monitoring station 2.

on 10 Chiling Street is June 15, 2020. We use the *Aqi* averages from July 2019 to May 2020 as the pre-12-month pollution exposure proxy for this house. The potential endogeneity problem between pollution and housing price can be alleviated to some extent by using this pre-12-month moving average air pollution exposure, although a DID estimation approach is still warranted as an identification strategy.

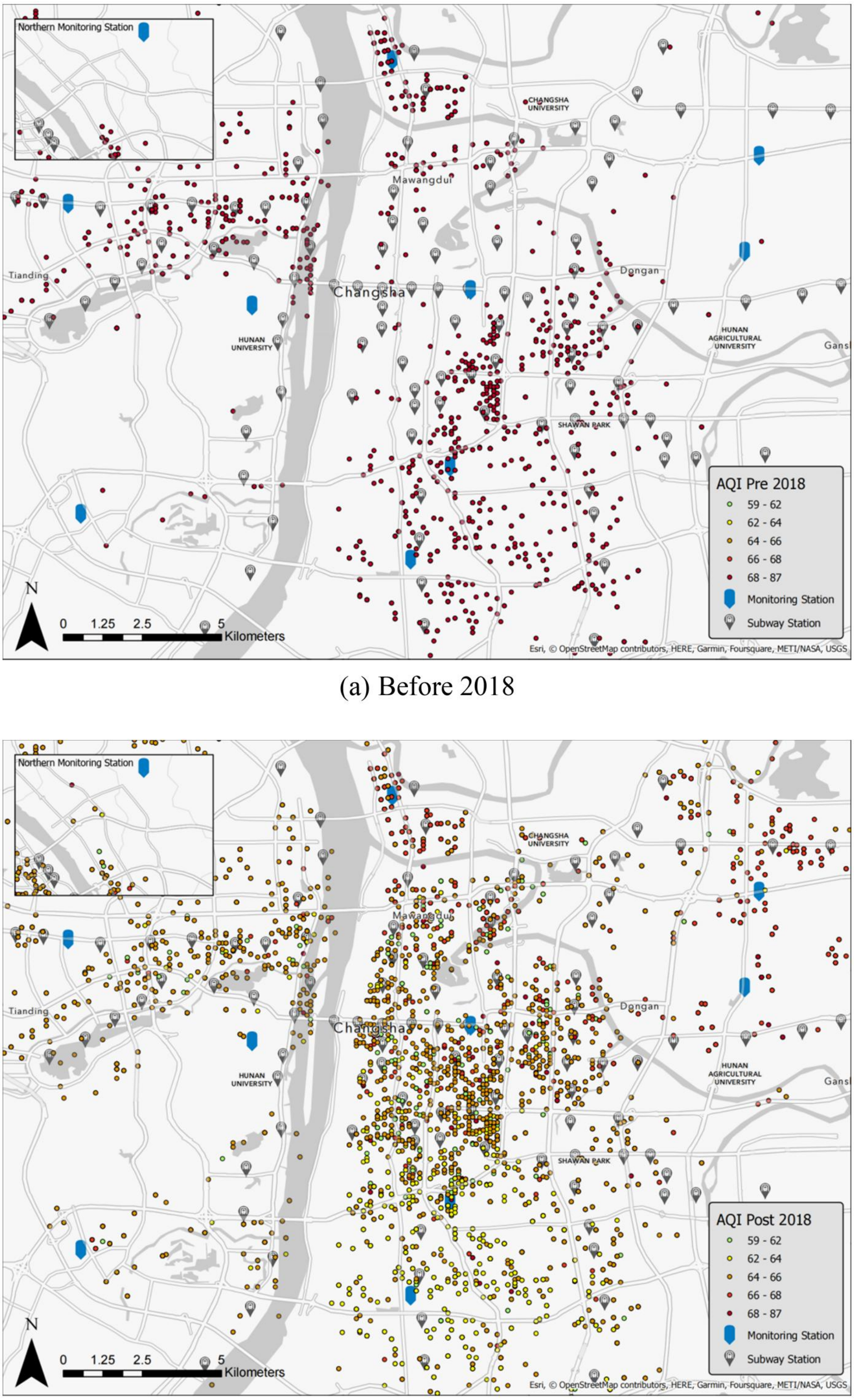
Figure 2 shows the monthly estimated *Aqi* of each dwelling unit before (Figure 2(a)) and after (Figure 2(b)) the year 2018 in Changsha city. Before the BSPC policy enforcement, the transacted dwelling units are almost dark red dotted, indicating the locations have high interpolated *Aqi* values or relatively heavy pollution. After 2018, the dots turn light red, yellow, or even green, indicating the interpolated *Aqi* values of the dwelling units' locations are decreasing, and the air quality improves.

Table 1 shows the descriptive statistics for the key variables of interest. The average dwelling unit sale price is slightly over 1 million Yuan, has approximately 98 square meters of area, is 10.7 years old, and is 1.71 kilometers from the nearest subway station. The average days on the market are 104, while approximately 78% of the units in the sample are sold after the introduction of the BSPC action plan.

4. Estimation results

4.1 Continuous Aqi Data Estimation

The first set of results estimated with Equations (1) and (2), based on Aqi_{it} as the continuous treatment variable, are presented in Table 2. The housing prices, Aqi_{it}, distance to the nearest subway station, and the time on the market are all in natural log form. Columns (1)-(3) report the regression results of air quality on housing prices measured in 10 thousand Yuan per square meter of living area, and columns (4)–(6) report the results for air quality on housing total prices (measured in 10 thousand Yuan). We control for the district and temporal fixed effects in both models.



(a) Before 2018

(b) After 2018

Figure 2. AQI (Air Quality Index) of transacted dwelling units in Changsha.

Table 1. Variable definitions and descriptive statistics.

Variable name	Variable description	Mean	Std Dev	Min	Max
Total price	Total transaction price (10 thousand Yuan)	101.036	64.058	10	2000
Price per Sq Meter	Unit price (10 thousand Yuan/square meter)	1.008	0.319	0.286	4.064
Aqi	Interpolated monthly Air Quality Index	64.717	23.215	31.825	133.391
Estimated Aqi	*Aqi* average of 12 months prior to the transaction month	67.364	5.354	57.334	86.155
BSPC	Dummy variable for post-date of the Blue Sky Protection Campaign action plan (June 27, 2018)	0.784	0.412	0	1
Area	Property area (square meters)	97.762	39.452	17.93	765
Age	Age of the property at the time of the transaction	10.688	5.645	0	55
Subway Distance (km)	The distance to the nearest subway station (kilometer)	1.711	1.660	0.018	28.159
Time on market	Transaction days (days on the market)	103.943	129.575	1	1592
District GDP	District gross domestic products (100 million Yuan)	1488.91	485.235	582.19	2360
District population	District population (10 thousand people)	102.494	30.657	57.58	157.98

The number of observations of *Age* is 27,856, and the number of observations of other variables is 28,004.

Table 2. Effect of Aqi on housing prices.

	ln(*price per sq meter*)			ln(*total price*)		
	(1)	(2)	(3)	(4)	(5)	(6)
ln(*Aqi*)	−0.424***		−2.233***	−0.475***		−1.999***
	(−5.21)		(−4.25)	(−5.94)		(−4.16)
BSPC	—	−0.003	−9.454***		−0.036***	−7.942***
		(−0.39)	(−3.87)		(3.47)	(−3.52)
ln*(Aqi)* × *BSPC*			2.189***			1.831***
			(3.87)			(3.50)
ln(*Subway Distance*)	−0.083***	−0.082***	−0.085***	−0.071***	−0.069***	−0.072***
	(−4.47)	(−4.50)	(−4.35)	(−3.89)	(−3.92)	(−3.81)
ln(*TOM*)	−0.016***	−0.016***	−0.016***	−0.018***	−0.018***	−0.018***
	(−3.67)	(−3.62)	(−3.70)	(−4.00)	(−3.94)	(−4.01)
Area	0.001***	0.001***	0.001***	0.011***	0.011***	0.011***
	(4.71)	(4.64)	(4.68)	(35.41)	(35.35)	(35.57)
Age	−0.021***	−0.021***	−0.021***	−0.021***	−0.021***	−0.021***
	(−10.91)	(−10.89)	(−11.04)	(−10.75)	(−10.37)	(−10.85)
ln*(District GDP)*	−0.115	−0.136	0.099	−0.083	−0.107	0.096
	(−1.32)	(−1.48)	(0.90)	(−0.99)	(−1.37)	(0.532)
ln*(District Population)*	0.317**	0.310***	0.279**	0.406***	0.398***	0.375***
	(3.46)	(3.48)	(2.68)	(4.84)	(4.98)	(3.86)
R^2	0.395	0.394	0.396	0.757	0.757	0.756

Note: (1) The number of observations are 27,856; (2) The *t*-statistic value of cluster standard error at the district level is reported in parentheses; (3) All models include temporal and district fixed effects. (4) ***, **, and * indicate significance at 1%, 5%, and 10% significance levels, respectively.

The results in columns (1) and (4) indicate that a higher *Aqi* index (with greater air pollution) is associated with lower housing prices in the area, which confirms the hypothesis that air pollution can depreciate the housing property value. A 10 percent increase in *Aqi* leads to a 4.24% and 4.57% decrease in unit price and total price, respectively. The results in columns (2) and (5) indicate that there is no difference in the housing unit price before or after the BSPC policy. However, after June 2018, the average total price of dwelling units in Changsha City decreased by about 3.6%. The results in columns (3) and (6) show that the estimated coefficient of the interaction term of *Aqi* and BSPC is significantly positive at the 1% significance level. Considering that the *Aqi* index in the model is the moving average of the *Aqi* value 12 months before the transaction month, the positive estimate of this interaction term indicates that the dwelling units located in previously severely air-polluted areas can see their housing prices increase more than the houses located in relatively light air-polluted areas after the BSPC was enacted, with larger impacts on unit price than total price. Combining the impact of *Aqi* and the interaction term, we find that BSPC policy can mitigate the negative impact of air pollution on housing value.

The distance to the nearest subway station entrance has a negative effect on housing prices. A 10 percent increase in this distance will lead to about a 0.72%–0.85% decrease in housing prices, holding all other housing price determinants constant. The dwelling units' area, age, transaction days, and district population can also significantly affect housing prices. The housing area, the TOM, and housing age are all negatively correlated with the housing price.

4.2 Dummy variable Specification and Dynamic Version Estimation Results

We next replace the continuous *Aqi* variable with a dummy variable that allows us to test the difference in the effects of air quality on housing prices between houses where air quality is above and below the 50th percentile. As shown in Table 3, the housing prices of dwelling units in locations with above-median pollution levels increased more than those in areas with below-median pollution levels after the BSPC was enacted. The results are consistent with those in the continuous *Aqi* specification models.

The coefficient estimates α_p and its 95% confidence interval of the dynamic version of specification based on Equation (4) are shown in Figure 3. There is no significant difference in the *Aqi* impact on housing values for periods before the BSPC. About five months after the BSPC, the policy impact on the *Aqi*-housing value relationship becomes significantly positive. This lag effect is sensible. The central government announced BSPC on June 27, 2018. The city government still needed time to work out the local implementation and monitoring plan. It likely took some time for the policies to be implemented by the city government, have effects on air pollution, and, in turn, impact the housing market.

Table 3. Effects of pollution on housing prices using Aqi $D_{50,i}$ dummy.

	(1) ln(*price per sq meter*)	(2) ln(*total price*)
Dummy for pollution above the 50th percentile	−0.020(−0.047)	−0.020(−0.41)
BSPC	−0.056***(−4.54)	−0.091***(−6.74)
Dummy for pollution above the 50th percentile ×*BSPC*	0.064**(2.27)	0.061*(1.97)
ln(*Subway Distance*)	−0.079***(−3.76)	−0.066***(−3.13)
ln(*Time on market*)	−0.015***(−3.59)	−0.018***(−3.96)
Area	0.001***(4.52)	0.011***(35.05)
Age	−0.021***(−10.55)	−0.021***(−10.38)
ln*(District GDP)*	0.073(0.77)	0.094(0.96)
ln*(District Population)*	0.206***(3.54)	0.299***(6.51)
R^2	0.398	0.758

Notes: (1) The number of observations are 27,856; (2) The t-statistic values (based on clustered standard errors at the district level) are reported in parentheses; (3) All models control for temporal and district fixed effects; (4) ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

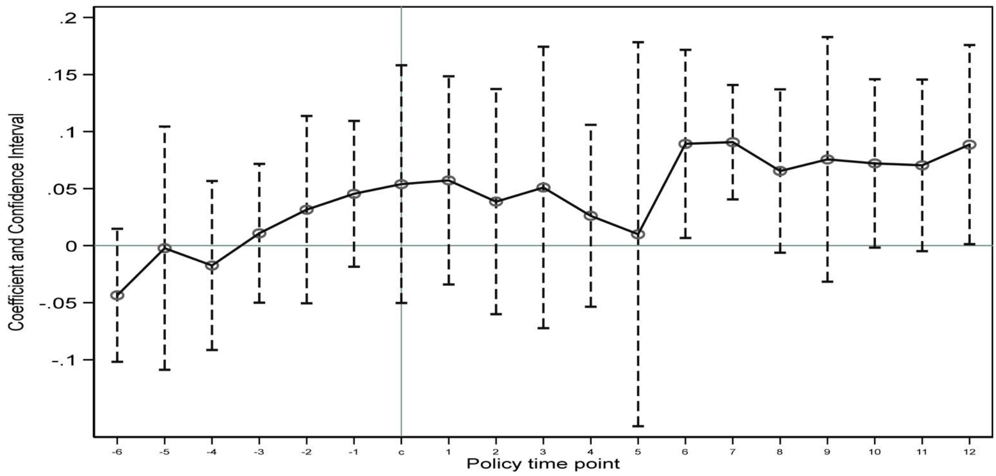


Figure 3. The relationship between the Aqi and housing value across time period.

It is worth noting that the coefficients become insignificant at a 5% significance level (but significant at a 10% level) after some time. This may be because people have formed new expectations for air quality after perceiving the improvement of air pollution and converting it into positive feedback on real estate value, and the improvement of air pollution has shifted from optimism to indifference.

4.3 Robustness Check

To examine the robustness of our results, we first use the log of the *Aqi* averaged throughout the pre-treatment period and then the main pollutant (PM2.5 and SO_2) concentration index as the proxy variable of air quality. In addition, we adjust the time horizon by averaging the air quality index over the prior 3, 6, and 9 months at the dwelling unit level. We add the point of interest (POI) information for each dwelling unit at different distance scales into the model to control the development status of the units' location. We also follow Turnbull and Dombrow (2006) and implement a 3 stage least squares (3SLS) approach to address the potential simultaneity between prices and TOM.

4.3.1 Time-Invariant Aqi Index

The estimation results from the specification using the log of the *Aqi* averaged throughout the pre-treatment period as the proxy of *Aqi* are shown in Table 4. The results are consistent with the baseline model.

4.3.2 Pollutants (PM2.5 and SO_2) Effects

The BSPC has a clear policy goal to decrease the PM2.5 and SO_2 pollutant concentrations. It has aimed to significantly reduce the total emissions of major atmospheric pollutants, greenhouse gases, and fine particulate matter (PM2.5) concentration, thus considerably improving air quality. By 2020, the plan had targeted to reduce the total sulfur dioxide emissions by more than 15%, compared to the level recorded in 2015.[11]

Table 4. Results of using the Aqi averaged throughout the pre-treatment period.

	(1)	(2)
	ln(*price per sq meter*)	ln(*total price*)
Time-invariant Aqi	−1.187(−0.53)	−0.527(−0.22)
BSPC	−14.337***(−5.29)	−12.663***(−4.09)
Time-invariant Aqi × *BSPC*	3.309***(5.31)	2.915***(4.09)
R^2	0.398	0.758

Notes: (1) The number of observations are 27,856; (2) The *t*-statistic values (based on clustered standard errors at the district level) are reported in parentheses; (3) All models control for temporal and district fixed effects; (4) ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 5. Effect of PM2.5 and SO_2 pollutants on housing prices.

	PM2.5		SO_2	
	ln(*price per sq meter*)	ln(*total price*)	ln(*price per sq meter*)	ln(*total price*)
ln(*Estimated pollutant index*)	−1.685*** (−6.97)	−1.597*** (−6.67)	−0.909*** (−7.55)	−0.931*** (−8.50)
BSPC	−7.501*** (−11.95)	−6.694*** (−12.54)	−2.787*** (−7.15)	−2.775*** (−7.42)
ln(*Estimated pollutant index*) ×*BSPC*	1.905*** (11.94)	1.691*** (12.50)	1.108*** (7.18)	1.089*** (7.38)
R^2	0.401	0.759	0.402	0.759

Note: (1) The number of observations is 27,856; (2) The I-statistics (based on clustered standard errors at the district level) are reported in parentheses; (3) All models include temporal fixed effects and district fixed effects. (4) ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Here, we use the PM2.5 and SO_2 concentrations in a separate regression model as the proxy variables for air quality to replace *Aqi*. The estimation results of both unit price and total price models (shown in Table 5) for each of the two pollutant concentration models are consistent with the baseline model.

4.3.3 Adjustment of Time Horizon

Considering that prior longer-term air quality readings are the available information at the time of the dwelling unit purchase decisions, we adjust the time horizon to 9, 6, and 3 months over which we average the air quality index. The results in Table 6 show that the interaction term of *Aqi* and *BSPC* is positive and statistically significant. Our benchmark estimates are robust. The estimates monotonically increase as we extend the time frame for averaging the *Aqi*, suggesting that home buyers tend to be more wary of air pollution if it has been a persistent issue in the neighborhood leading up to the transaction. This finding is consistent with the analysis of the real estate market in Tehran, Iran, by Amini et al. (2022).

4.3.4 Using the POI Information

To address the endogeneity issue further, we calculate the number of restaurants within 1-3 kilometers of the location of the dwelling units by using the POI data provided by Gaode Navigation. On a map, a POI can represent a restaurant, a building, a shop, or a scenic spot, for example. We further use the number of restaurants within a range of 1-3 kilometers from the dwelling unit in the POI data as a proxy for the economic development level of the location where the dwelling unit is located and include it as a control variable in the regression model. The regression results presented in Table 7 indicate that our baseline model results are robust.

Table 6. Effect of Aqi of different time horizons on housing prices.

	(1) 3 months		(2) 6 months		(3) 9 months	
	ln(*price per sq meter*)	ln(total price)	ln(*price per sq meter*)	ln(*total price*)	ln(price per sq meter)	ln(*total price*)
ln(*Estimated Aqi*)	−0.225*** (−28.66)	−0.209*** (−21.34)	−0.317*** (−13.03)	−0.305*** (−11.35)	−0.299** (−4.00)	−0.297** (−3.49)
BSPC	−1.084*** (−22.83)	−1.009*** (−18.19)	−1.564*** (−16.99)	−1.484*** (−15.68)	−1.576** (−4.24)	−1.507** (−3.92)
ln(*Estimated Aqi*) ×*BSPC*	0.243*** (21.66)	0.218*** (17.65)	0.350*** (17.22)	0.324*** (16.07)	0.362** (4.25)	0.338** (3.84)
R^2	0.402	0.757	0.401	0.759	0.395	0.757

Note: (1) The number of observations are 27,856; (2) The I-statistics (based on clustered standard errors at the district level) are reported in parentheses; (3) All models include temporal fixed effects and district fixed effects. (4) ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 7. Effects of pollution on housing prices controlling for the number of nearby restaurants.

	(1) 1 kilometer		(2) 2 kilometer		(3) 3 kilometer	
	ln(*price per sq meter*)	ln(total price)	ln(*price per sq meter*)	ln(*total price*)	ln(*price per sq meter*)	ln(*total price*)
ln(*Estimated Aqi*)	−2.226*** (−4.39)	−0.206*** (−4.27)	−2.187*** (−4.33)	−1.966*** (−4.22)	−2.161*** (−4.54)	−1.939*** (−4.35)
BSPC	−9.483*** (−3.86)	−7.961*** (−3.50)	−9.220*** (−3.79)	−7.772** (−3.43)	−9.012*** (−3.71)	−7.574** (−3.29)
ln(*Estimated Aqi*) ×*BSPC*	2.196*** (3.86)	1.835*** (3.49)	2.135*** (3.79)	1.792** (3.41)	2.087*** (3.71)	1.746** (3.27)
ln(*number of restaurants*)	0.324 (1.32)	0.209 (1.00)	0.053** (2.93)	0.039* (2.15)	0.082*** (3.92)	0.681** (2.82)
R^2	0.407	0.759	0.411	0.760	0.422	0.763

Note: (1) The number of observations are 27,856; (2) The I-statistics (based on clustered standard errors at the district level) are reported in parentheses; (3) All models include temporal fixed effects and district fixed effects. (4) ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively. (5) The estimated results of other explanatory variables are omitted for ease of presentation but are available upon request from the authors.

4.3.5 Adjustments for TOM

Property prices (Price) and the TOM are simultaneously determined (Hayunga & Pace, 2019). Houses on the market for longer are expected to sell for lower prices, while lower-priced houses are also likely to sell more quickly. To address this simultaneity between price and TOM, we followed Turnbull and Dombrow (2006) and estimated the following system of equations using 3SLS:

$$\ln Price_{ijt} = \alpha_1 + X'\beta_1 + \gamma \ln TOM_{ijt} + \varphi \ln LDensity_{ijt} + \theta_1 S_j + \rho_1 T_t + \epsilon_1 \tag{7}$$

$$\ln TOM_{ijt} = \alpha_2 + X'\beta_2 + \delta \ln Price_{ijt} + \vartheta \ln COMP_{ijt} + \theta_2 S_j + \rho_2 T_t + \epsilon_2 \tag{8}$$

where X represents structural and transactional attributes (including ln(*Aqi*)); *COMP* is a proxy for the number of competing homes for sale in the local market; *LDensity* is the listing density defined as the number of competing houses on the market per day; S denotes the geographical submarket fixed effects, and T signifies the time fixed effects. In this system of two equations, the inclusion of *COMP* in the *TOM* Equation (8) but not in the Price Equation (7) identifies the Price Equation (7) by satisfying the exclusion restriction. Similarly, the *TOM* equation is identified because *LDensity* is in the Price equation but not in the *TOM* equation. We thus use a 3SLS approach that allows us to (i) control for the simultaneity between *Price* and *TOM* and (ii) obtain more reliable standard errors by accounting for the correlation between the errors of the two equations in the system.

Given that we find the estimated coefficients on *LDensity* and *COMP* statistically significant, we conclude that both equations are identified, allowing us to obtain unbiased and more efficient estimates using this 3SLS approach. The results are shown in Table 8, and the estimation results of both unit price and total price models estimated via 3SLS are also consistent with the results from the baseline model estimates shown in Table 2.

4.3.6 Controlling for the Covid-19 Impacts

The data sample in this paper includes the dates of the outbreak period of Covid-19 in early 2020. COVID-19 in Changsha City during the epidemic was sporadic, and all districts

Table 8. TOM 3SLS estimation results of pollution on house prices.

	ln(*price per sq meter*)		ln(*total price*)	
	ln(*TOM*)	ln(*price per sq meter*)	ln(*TOM*)	ln(*total price*)
ln(*Comp*)	1.301*** (46.62)		1.548*** (20.93)	
ln(*LDensity*)		−0.069*** (−23.39)		−0.052*** (−15.30)
ln(*TOM*)		−0.014*** (−14.51)		−0.017*** (−15.28)
ln(*price per sq meter*)	17.579*** (17.15)			
ln(*total price*)			27.463*** (9.40)	
ln(*Estimated Aqi*)	39.222*** (12.42)	−2.232*** (−18.09)	54.896*** (7.77)	−2.000*** (−13.86)
BSPC	147.25*** (10.60)	−8.403*** (−14.37)	195.611*** (6.73)	−7.143*** (−10.44)
BSPC× ln(*Estimated Aqi*)	−34.048*** (−10.58)	1.944*** (14.34)	−45.014*** (−6.71)	1.644*** (10.37)
ln(*Subway Distance*)	1.217*** (13.88)	−0.070*** (−38.63)	1.646*** (8.09)	−0.061*** (−28.54)
Area	−0.021*** (−15.74)	0.001*** (34.56)	−0.295*** (−9.41)	0.011*** (268.30)
Age	0.391*** (17.45)	−0.022*** (−85.44)	0.613*** (9.55)	−0.022*** (−73.23)
ln*(District GDP)*	−2.053** (−2.21)	0.122** (2.32)	−3.005* (−1.76)	0.113* (1.85)
ln*(District Population)*	−4.752*** (−7.74)	0.268*** (8.62)	−10.107*** (−6.88)	0.366*** (10.07)

Notes: (1) The number of observations is 27,856; (2) The *z*-statistic values (based on clustered standard errors at the district level) are reported in parentheses; (3) ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Table 9. Effect of air pollution on housing prices controlling for Covid-19 impacts.

	Including interaction of fixed effects		Dropping the observations after 2020	
	ln(*price per sq meter*)	ln(*total price*)	ln(*price per sq meter*)	ln(*total price*)
ln(*Estimated pollutant index*)	−2.400*** (−4.51)	−2.159*** (−4.07)	−2.104*** (−4.04)	−1.915*** (−3.97)
BSPC	−9.870*** (−4.06)	−8.369*** (−3.48)	−10.148*** (−7.91)	−8.840*** (−9.60)
ln(*Estimated pollutant index*) ×*BSPC*	2.285*** (4.05)	1.930** (3.46)	2.350*** (7.94)	2.040*** (9.65)
Obs	27,856	27,856	9,743	9,743
R^2	0.407	0.760	0.437	0.776

Note: (1) The l-statistic values(based on clustered standard errors at the district level) are reported in parentheses; (2) ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

were randomly affected. To control for the potential impact of the epidemic on the housing market, we include an interaction term between temporal fixed effects and district fixed effects. We also alternatively drop observations after 2020. The results of these regressions are reported in Table 9. The estimation results of both models are still robust.

4.4 Some Further Analysis

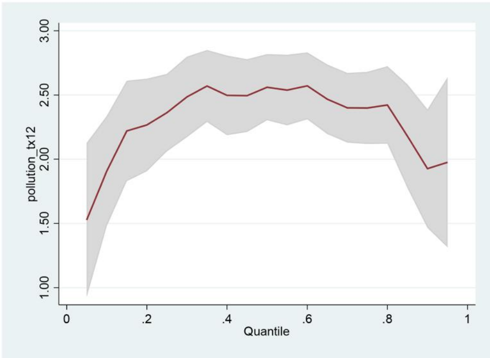
4.4.1 Heterogeneity of Housing Prices

The implicit prices of specific housing characteristics may differ significantly across the distribution (Liao & Wang, 2012). The impact of air quality on housing prices may be heterogeneous due to the house values. Thus, we use a quantile regression model to test whether there are differences in air quality effects on housing prices for dwelling units. Figures 4(a and b) show the coefficients on our main variables of interest, ln(*Estimated pollutant index*) ×*BSPC*, at these quantiles of unit price and total price, respectively.

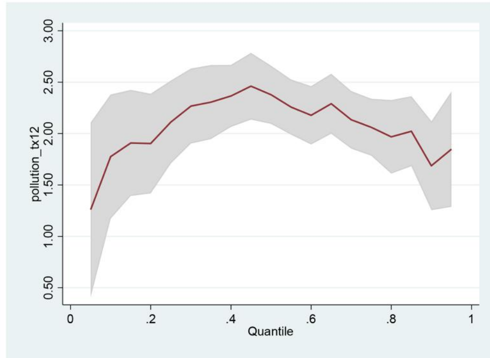
The results indicate that there are differences in the effect of air quality on house prices across quantiles, as the coefficient varies when moving from the lower tail to the upper tail of the distribution. Specifically, the results show that air quality has a significant impact on house prices across the entire range of the output distribution, but this effect becomes more pronounced as one moves from the lower end to the middle and upper end of the distribution. Thus, the dwelling units at the middle and higher tails of the distribution (e.g. dwelling units with relatively higher housing prices) benefit more from the BSPC. More specifically, the relatively cheaper houses at the lower tail of the distribution (e.g. quantiles 0.10–0.20) benefit less from the policy. For the houses in the middle of the distribution (e.g. quantile 0.4–0.6), the coefficient of interest increases to the highest level. Thus, these houses benefit more from the policy.[12]

4.4.2 Anticipation Effects Test

It is possible that the policy implementation was expected, and buyers adjusted their behavior even before the pollution levels decreased after July 2018. If so, the positive effect we find may reflect the optimism or anticipation of the BSPC policy. To explore this, we construct a series of dummy variables that indicate whether the time period is between January and June 2018 (6 months before BSPC, *DB6*), between July and December 2018 (6 months after BSPC, *DA6*), in 2019 (*DA2019*), in 2020 (*DA2020*), and in



(a) Unit price



(b) Total price

Figure 4. Quantile regression estimation results of air pollution on housing prices.

Table 10. Anticipation effects test.

	(1) 6 months		(2) 9 months		(3) 12 months	
	ln(*price per sq meter*)	ln(*total price*)	ln(*price per sq meter*)	ln(*total price*)	ln(*price per sq meter*)	ln(*total price*)
ln(*Aqi of X-month prior to BSPC*) ×*DB6*	0.290 (0.88)	0.297 (-0.88)	0.180 (0.78)	0.036 (0.12)	0.223 (0.370)	0.199 (0.68)
ln(*Aqi of X-month prior to BSPC*) ×*DA6*	1.323* (2.13)	1.411* (2.32)	1.082* (1.97)	1.118** (2.43)	1.107* (1.95)	1.185** (2.60)
ln(*Aqi of X-month prior to BSPC*) ×*DA2019*	1.506** (3.15)	1.101** (2.45)	1.154** (2.51)	0.686 (1.39)	1.197** (2.56)	0.761 (1.46)
ln(*Aqi of X-month prior to BSPC*) ×*DA2020*	3.213*** (4.02)	2.747*** (3.58)	2.918*** (3.73)	2.452** (3.24)	3.048*** (3.78)	2.605** (3.22)
ln(*Aqi of X-month prior to BSPC*) ×*DA2021*	3.552*** (3.83)	3.001** (3.16)	3.527*** (3.85)	2.941** (3.24)	3.663*** (4.01)	3.086** (3.36)
R^2	0.399	0.758	0.399	0.758	0.399	0.758

Note: (1) The number of observations are 27,856; (2) The t-statistic values (based on clustered standard errors at the district level) are reported in parentheses; (3) All models include temporal fixed effects and district fixed effects. (4) ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

2021 (*DA2021*). We take the average *Aqi* value of each dwelling unit's past X-month (where X takes the values 6, 9, and 12) prior to BSPC as the air pollution variable. We then test the anticipation effect by estimating Equation (2) using these proxies, together with their interaction terms and other control variables. An insignificant coefficient on the interaction term ln(*Aqi of X-month prior to BSPC*) ×DB6 suggests that buyers did not change their behavior in anticipation of the policy in the following period. For our hypotheses to be supported, the coefficients on the other interactions should be significantly positive. These results are illustrated in Table 10.

The estimation results in Table 10 show that the interaction of the *Aqi* and DB6 variables is insignificant in each specification, implying that there is no anticipation effect. Note also that the coefficients on the other interactions remain significantly positive, supporting our hypothesis. As time goes by, the positive effect gradually strengthens, confirming the hypothesis that BSPC has a significant effect, which can help the housing prices of the dwelling units in districts with higher average pollution levels before BSPC to increase more than that of dwelling units in districts with lower air pollution before the policy.

5. Conclusion

Efforts to reign in high pollution levels can take various forms, including taxing polluting firms, imposing pollution quotas, and other approaches (Baumol & Oates, 1988). In China, the BSPC of 2018 mandated decreased emissions of pollutants, especially PM2.5 and SO_2. This was to be accomplished with changes in transportation infrastructure planning, implementing additional green energy sources, and with changes in land use to discourage pollution. These types of land use and infrastructure policies were expected to lead to greater desirability for living in the polluted areas, which should lead to higher house prices in these neighborhoods. The main hypothesis we test in this paper is that the BSPC regulations translated into higher housing prices in areas that were previously exposed to greater pollution in Changsha, China.

We first demonstrate some graphical depictions of the trends in pollution in Changsha before versus after the 2018 BSPC initiative. There appear to be downward trends in pollution levels after the implementation of BSPC. But more than visual evidence is needed to conclusively validate the hypothesis that the regulations caused higher house prices. Thus, we estimate a hedonic house price model using a DID identification strategy to address this hypothesis.

Specifically, we find that there is between a 1.8 and 2.2% rise in house prices associated with pollution after versus before the BSPC regulations. For houses that were exposed to greater than the 50th percentile of all types of pollution, the BSPC regulations' effect on house prices is approximately 6 percent. But when focusing exclusively on PM2.5, the house price effect is between 1.11 and 1.91 percent. This "treatment effect" is statistically significant in all specifications. It is clear that the BSPC regulations had a positive and significant effect on house prices in Changsha.

Prior known data limitations prevented this type of thorough causal analysis. We build upon the available pollution emissions data in Changsha for 10 air quality monitoring stations and interpolate an estimated pollution level for each house in our sample that sold during our study period. We aggregate our interpolated pollution estimates from hourly data up to the monthly level and use averages over the prior 12 months preceding each property sale to estimate pollution exposure for each house. This interpolation and aggregation enable us to associate a unique pollution exposure level for each house location at the time of sale.

In addition to using the DID identification strategy to control for the potential endogeneity of the variable of interest, we also check the robustness of our results via constructing new *Aqi* variables by adjusting the time horizon to 9, 6, and 3 months over which we average the air quality index. We also use POI information to control for restaurants as a proxy for economic activity. With a 3SLS approach, we are able to address the potential simultaneity of TOM with house prices. Finally, we also consider the possible impact of Covid-19. The results of these robustness checks are consistent with those from our base specifications. We also obtain the regression coefficient at different quantiles of housing prices and find that dwelling units with relatively higher housing prices can benefit more from the BSPC policy, and tests of the possible anticipation effects are robust.

Our findings have important implications for environmental policy in Changsha, China in general, and more broadly throughout Asia. One way to generate more housing wealth for residents is to lower pollution exposure, and since the BSPC initiative was effective in raising house prices, similar regulations could have additional attractive effects. However, these housing wealth effects need to be considered more broadly against the impacts on commercial properties from these types of pollution restrictions. In other words, one might expect these types of regulations in one particular city or country to make that location less desirable for some polluting businesses to locate. These types of restrictions could drive out some potential polluting business tenants and, therefore, lower the net operating income on commercial units, especially where there are alternative locations (in China or elsewhere) without as strict regulations. In this situation, there could be detrimental effects on commercial property values that could potentially offset the gains to homeowners. But, further studies of these types of forces in China are needed to determine the net effects.

Notes

1. See https://english.www.gov.cn/state_council/ministries/2018/02/04/content_281476036003188.htm.
2. See http://www.gov.cn/xinwen/2018-02/01/content_5262720.htm
3. The national ecological environment quality profile in 2020, The Ministry of Ecological Environment.
4. Data source: News report released by Ecology and Environment Department of Hunan, http://sthjt.hunan.gov.cn/sthjt/xxgk/xwdt/szxw/202009/t20200903_13698104.html.
5. We estimate one specification with the total residential price as the dependent variable, and separately, another specification with the unit price as the dependent variable (measured in 10,000 yuan per square meter).
6. See Qian (2008), Nunn and Qian (2011), and Feng et al. (2023) for similar estimation strategies.
7. In 2021, Changsha had a total permanent population of 10.2393 million and a GDP of 1327.07 billion yuan. The data comes from the National Bureau of Statistics and Changsha Municipal Bureau of Statistics.
8. GCJ-02 is a coordinate system of the Geographic Information System developed by the National Bureau of Surveying and Mapping of China.
9. Therefore, the monitoring data of air quality stations is the primary data for evaluating air quality. The assessment of air quality is obtained by urban air quality monitoring stations through fixed-point, continuous or timed sampling measurement, and analysis of pollutants present in the atmosphere and air. CNEMC's air quality monitoring network consists of more than 1400 stations in China (Zheng et al., 2019). The air quality monitoring stations are located in the built-up areas of each city, with relatively uniform distribution, covering all built-up areas.
10. The data from other monitoring stations have similar patterns.
11. See the details about the plan at: https://www.gov.cn/zhengce/content/2018-07/03/content_5303158.htm or http://english.www.gov.cn/policies/latest_releases/2018/07/03/content_281476207708632.htm.
12. The authors thank an anonymous reviewer for pointing out that this interpretation is conditional on the rank invariance assumption, which is a strong assumption to break but hard to test in reality because a treatment can make a subject move up in ranking in the distribution. For more information, please see Liao and Zhao (2019) and Callaway and Li (2019).

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References

Amini, A., Nafari, K., & Singh, R. (2022). Effect of air pollution on house prices: Evidence from sanctions on Iran. *Regional Science and Urban Economics*, *93*, 103720. https://doi.org/10.1016/j.regsciurbeco.2021.103720

Baumol, W. J., & Oates, W. (1988). *The theory of environmental policy*. Cambridge University Press. https://doi.org/10.1017/CBO9781139173513

Cai, S., Wang, Y., Zhao, B., Wang, S., Chang, X., & Hao, J. (2017). The impact of the "air pollution prevention and control action plan" on pm2.5 concentrations in jing-jin-ji region during 2012–2020. *The Science of the Total Environment*, *580*(FEB.15), 197–209. https://doi.org/10.1016/j.scitotenv.2016.11.188

Callaway, B., & Li, T. (2019). Quantile treatment effects in difference in differences models with panel data. *Quantitative Economics*, *10*(4), 1579–1618. https://doi.org/10.3982/QE935

Chay, K. Y., & Greenstone, M. (2005). Does air quality matter? Evidence from the housing market. *Journal of Political Economy*, *113*(2), 376–424. https://doi.org/10.1086/427462

Chen, D., & Chen, S. (2017). Particulate air pollution and real estate valuation: Evidence from 286 Chinese prefecture-level cities over 2004–2013. *Energy Policy*, *109*, 884–897. https://doi.org/10.1016/j.enpol.2017.05.044

Chen, J., Hao, Q., & Yoon, C. (2018). Measuring the welfare cost of air pollution in Shanghai: Evidence from the housing market. *Journal of Environmental Planning and Management*, *61*(10), 1744–1757. https://doi.org/10.1080/09640568.2017.1371581

Chen, S., & Jin, H. (2019). Pricing for the clean air: Evidence from Chinese housing market. *Journal of Cleaner Production*, *206*, 297–306. https://doi.org/10.1016/j.jclepro.2018.08.220

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *The American Economic Review*, *109*(12), 4178–4219. https://doi.org/10.1257/aer.20180279

Diao, M., Qin, Y., & Sing, T. F. (2016). Negative externalities of rail noise and housing values: Evidence from the cessation of railway operations in Singapore. *Real Estate Economics*, *44*(4), 878–917. https://doi.org/10.1111/1540-6229.12123

Fan, J., Lin, Z., Zhou, L. (2023). The value of clean air: Evidence from Chinese housing markets. *MIT Asia Real Estate Initiative Inaugural Symposium*.

Feng, Y., Ning, M., Lei, Y., Sun, Y., Liu, W., & Wang, J. (2019). Defending blue sky in China: Effectiveness of the "Air Pollution Prevention and Control Action Plan" on air quality improvements from 2013 to 2017. *Journal of Environmental Management, 252*, Article 109603. https://doi.org/10.1016/j.jenvman.109603

Feng, P., Yasar, M., & Cohen, J. P. (2023). Do higher house prices crowd-out or crowd-in manufacturing? A spatial econometrics approach. *The Journal of Real Estate Finance and Economics*. Advance online publication. https://doi.org/10.1007/s11146-023-09956-x

Greenstone, M., & Hanna, R. (2014). Environmental regulations, air and water pollution, and infant mortality in India. *American Economic Review*, *104*(10), 3038–3072. https://doi.org/10.1257/aer.104.10.3038

Hanna, R., & Oliva, P. (2015). The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics*, *122*, 68–79. https://doi.org/10.1016/j.jpubeco.2014.10.004

Hao, Y., & Zheng, S. (2017). Would environmental pollution affect home prices? An empirical study based on china's key cities. *Environmental Science and Pollution Research International*, *24*, 24545–24561. https://doi.org/10.1007/s11356-017-0073-4

Hayunga, D. K., & Pace, R. K. (2019). The impact of TOM on prices in the US housing market. *The Journal of Real Estate Finance and Economics*, *58*(3), 335–365. https://doi.org/10.1007/s11146-018-9657-0

He, Y., & Collins, A. R. (2020). Does environmental pollution affect metropolitan housing prices? Evidence from Guangzhou, China (1987-2014). *Applied Economics Letters*, *27*(3), 213–220. https://doi.org/10.1080/13504851.2019.1613485

He, Y., Lai, Z., & Liao, N. (2024). Evaluating the effect of low-carbon city pilot policy on urban pm2.5: Evidence from a quasi-natural experiment in China. *Environment, Development and Sustainability*, *26*(2), 4725–4751. https://doi.org/10.1007/s10668-023-02906-w

He, J., Liu, H., & Salvo, A. (2019). Severe air pollution and labor productivity: Evidence from industrial towns in China. *American Economic Journal: Applied Economics*, *11*(1), 173–201. https://doi.org/10.1257/app.20170286

Isen, A., Rossin-Slater, M., & Walker, W. R. (2017). Every breath you take—Every dollar you'll make: The long-term consequences of the clean air act of 1970. *Journal of Political Economy*, *125*(3), 848–902. https://doi.org/10.1086/691465

Jiang, X., Fu, W., & Li, G. (2020). Can the improvement of living environment stimulate urban Innovation?—Analysis of high-quality innovative talents and foreign direct investment spillover effect mechanism. *Journal of Cleaner Production*, *255*, Article 120212. https://doi.org/10.1016/j.jclepro.2020.120212

Jiang, X., Li, G., & Fu, W. (2021). Government environmental governance, structural adjustment and air quality: A quasi-natural experiment based on the Three-year Action Plan to Win the Blue Sky Defense War. *Journal of Environmental Management*, *277*, 111470. https://doi.org/10.1016/j.jenvman.2020.111470

Kim, C. W., Phipps, T. T., & Anselin, L. (2003). Measuring the benefits of air quality improvement: A spatial hedonic approach. *Journal of Environmental Economics and Management*, *45*(1), 24–39. https://doi.org/10.1016/s0095-0696(02)00013-x

Liao, W.-C., & Wang, X. (2012). Hedonic house prices and spatial quantile regression. *Journal of Housing Economics*, *21*, 16–27. https://doi.org/10.1016/j.jhe.2011.11.001

Liao, W. C., & Zhao, D. (2019). The selection and quantile treatment effects on the economic returns of green buildings. *Regional Science and Urban Economics*, *74*, 38–48. https://doi.org/10.1016/j.regsciurbeco.2018.11.002

Li, S., Hui, E. C. M., Wen, H., & Liu, H. (2022). Does public concern matter to the welfare cost of air pollution? Evidence from Chinese cities. *Cities*, *131*, 103992. https://doi.org/10.1016/j.cities.2022.103992

Liu, R., Yu, C., Liu, C., Jiang, J., & Xu, J. (2018). Impacts of haze on housing prices: An empirical analysis based on data from Chengdu (China). *International Journal of Environmental Research and Public Health*, *15*(6), 1161. https://doi.org/10.3390/ijerph15061161

Li, K., Yuan, W., Li, J., & Ai, H. (2021). Effects of time-dependent environmental regulations on air pollution: Evidence from the changsha-zhuzhou-xiangtan region, China. *World Development*, *138*(1), Article 105267. https://doi.org/10.1016/j.worlddev.2020.105267

Mei, Y., Gao, L., Zhang, W., & Yang, F. A. (2021). Do homeowners benefit when coal-fired power plants switch to natural gas? Evidence from Beijing, China. *Journal of Environmental Economics and Management*, *110*, Article 102566. https://doi.org/10.1016/j.jeem.2021.102566

Nunn, N., & Qian, N. (2011). The potato's contribution to population and urbanization: Evidence from a historical experiment. *The Quarterly Journal of Economics*, *126*(2), 593–650. https://doi.org/10.1093/qje/qjr009

Qian, N. (2008). Missing women and the price of tea in China: The effect of sex-specific earnings on sex imbalance. *Quarterly Journal of Economics*, *123*(3), 1251–1285. https://doi.org/10.1162/qjec.2008.123.3.1251

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy*, *82*(1), 34–55. https://doi.org/10.1086/260169

Smith, V. K., & Huang, J. C. (1995). Can markets value air quality? A meta-analysis of hedonic property value models. *Journal of Political Economy*, *103*(1), 209–227. https://doi.org/10.1086/261981

Song, Y., Li, Z., Yang, T., & Xia, Q. (2020). Does the expansion of the joint prevention and control area improve the air quality?—Evidence from China's Jing-Jin-Ji region and surrounding areas. *The Science of the Total Environment*, *706*, 136034. https://doi.org/10.1016/j.scitotenv.2019.136034

Turnbull, G. K., & Dombrow, J. (2006). Spatial competition and shopping externalities: Evidence from the housing market. *The Journal of Real Estate Finance and Economics*, *32*(4), 391–408. https://doi.org/10.1007/s11146-006-6959-4

Wang, S., & Cai, Q. (2021). Are home buyers in Chinese cities concerned about air quality? Using panel data for 70 large and medium-sized cities from 2006 to 2016 as an example. *Journal of Housing and the Built Environment*, *36*(2), 685–704. https://doi.org/10.1007/s10901-020-09771-3

Wang, J., & Lee, C. L. (2022). The value of air quality in housing markets: A comparative study of housing sale and rental markets in China. *Energy Policy*, *160*, 112601. https://doi.org/10.1016/j.enpol.2021.112601

Wang, J. K., Wu, K. H., & Du, Y. H. (2022). Does air pollution affect urban housing prices? Evidence from 285 Chinese prefecture-level cities. *Journal of Cleaner Production*, *370*(10), 133480. https://doi.org/10.1016/j.jclepro.2022.133480

Zhang, H., Chen, J., & Wang, Z. (2021). Spatial heterogeneity in spillover effect of air pollution on housing prices: Evidence from China. *Cities*, *113*, 103145. https://doi.org/10.1016/j.cities.2021.103145

Zhang, P., & Wu, J. (2018). Impact of mandatory targets on PM2. 5 concentration control in Chinese cities. *Journal of Cleaner Production*, *197*, 323–331. https://doi.org/10.1016/j.jclepro.2018.06.189

Zheng, S., Zhang, X., Sun, W., & Wang, J. (2019). The effect of a new subway line on local air quality: A case study in Changsha. *Transportation Research Part D: Transport and Environment*, *68*, 26–38. https://doi.org/10.1016/j.trd.2017.10.004

Zou, G., Lai, Z., Li, Y., Liu, X., & Li, W. (2022). Exploring the nonlinear impact of air pollution on housing prices: A machine learning approach. *Economics of Transportation*, *31*, 100272. https://doi.org/10.1016/j.ecotra.2022.100272