The Value of Clean Air: Evidence from Chinese Housing Markets

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Abstract

This paper studies the value of clean air. By exploiting the cross-city variation in the implementation timing of China's clean air policy and using a panel dataset of 280 cities over 2003-2018, we find that the implementation of the clean air policy boosts housing values by 4.4%. The finding is robust to a series of potential issues, functional misspecifications, and falsification tests. We further examine whether the effect varies across different price-tier cities and changes over time, and we find evidence of such heterogeneous and dynamic effects.

Keywords: Clean air policy; Housing prices; China
JEL: Q58; R31

1 Introduction

In 1998, the Chinese government carried out the housing privatization reform, and the welfare public housing system was officially abolished. More and more Chinese households own their homes. By 2019, the homeownership rate of Chinese urban households reached 96%, and the total assets per household were RMB 3.179 million on average, of which housing assets accounted for more than 70% of the total household assets[1]. Therefore, housing prices have been of great importance to households' wealth in China.

The hedonic models have been widely used to estimate marginal implicit prices of embedded characteristics of properties in real estate literature (e.g. (Green and Hendershott, 1996), (Green and Lee, 2016), and (Rosen, 1974)). The embedded characteristics mainly include property attributes (e.g. housing vintage (Coulson and McMillen, 2008), floor level (Xiao et al., 2019), and living space (Agarwal et al., 2021)), neighborhood characteristics (e.g. open-space amenities (Shultz and King, 2001), industrial facilities (Grislain-Letrémy and Katossky, 2014), school (Sah et al., 2016), noise (Diao et al., 2016), and natural environment (Nicholls, 2019)), and location such as accessibility to transportation (McMillen and McDonald, 2004), distance to CBD (Liao and Wang, 2012), distance to super shopping center (Pope and Pope, 2015), and so on. With the rapid economic development and urbanization in China, environmental problems have become increasingly prominent with frequent smog. The effect of air pollution on housing prices has attracted wide attention in the literature. Air pollution has become an important factor for households to choose their residential locations, and cities with lower air pollution are associated with higher housing prices (Zheng et al., 2010; Grainger, 2012; Bento et al., 2015). For example, Chen et al. (2018) estimate the housing premium (the marginal willingness to pay (MWTP)) to be RMB 159/m^2 and RMB 238/m^2 respectively for a 1 µg/m^3 reduction in average SO_2 and PM_{10} in Shanghai. Freeman et al. (2019) find that Chinese households are willing to pay approximately $21.70 for a 1 µg /m^3 reduction in $PM_{2.5}$. Zheng et al. (2014) examine cross-boundary externalities

[1] The data comes from the "Survey on Assets and Liabilities of Chinese Urban Households in 2019".

of air pollution, and they find that a 10% decrease in air pollution from neighboring cities leads to a 0.76% increase in local housing prices.

Starting 2013, most cities in China implement clean air policy, which requires stringent measures on energy use and enterprise production technology. By exploiting the cross-city variation in the timing of implementation, we assess the effect of the clean air policy on housing prices. The clean air policy significantly improves air quality and benefits for health (Deschenes et al., 2017; Lee et al., 2018). For example, Lin and Zhu (2020) provide strong evidence that the implementation of clean air policy improves the green production efficiency of Chinese cities. Bezdek et al. (2008) also find that the clean air policy can achieve a win-win situation for both the environment and the economy. Many other studies examine how the clean air policy benefits for competitiveness (Porter and Van der Linde, 1995), technical change (Acemoglu et al., 2012), technological innovation (Jiang et al., 2020), and rationalization of industrial structure (Zhang et al., 2020). However, quite a few studies have documented the negative effect of the clean air policy. Stringent environmental regulations add substantial costs to the regulated enterprises and cut hiring rates in enterprises, which reduce overall employment (Walker, 2011; Curtis, 2018). The clean air policy also leads to regulated enterprises' output and profits reduction (Linn, 2010; Li et al., 2020). A recent paper by Agarwal et al. (2019) has explored the relationship between environmental policy (NOx Budget Trading Program) and housing prices in the United States. They find that housing prices shifted up in the regulated areas with low manufacturing intensity, whereas in the areas with high manufacturing intensity, housing markets were weakened. The reason is that in low-manufacturing-intensity areas, the effect of the environmental policy on housing prices is mainly through the healthy channel of reduced air pollution. However, the labor-market channel dominates the effect in high-manufacturing-intensity areas where loan application volume declined, rejection rate augmented, and the probability of loan default increased.

Using a sample of 280 cities in China from 2003 to 2018, we study the effect of clean air policy on housing prices by separating the sample into two groups: one group of cities implemented the clean air policy, while the other group did not. We then analyze the difference in housing prices between these two groups. After controlling for other observables, we find that the effects of the clean air policy on housing prices are economically important and statistically significant. In particular, housing prices in cities that have implemented the clean air policy are 4.4 percentage points higher than other cities, all else being equal. Our findings are robust to a series of potential issues and robustness checks. We further analyze whether the effect varies across different price-tier cities. Our findings suggest that the effect is much strong in high price-tier cities (5%) than median price-tier cities (3.8%) and low price-tier cities (2%). Based on the China Family Panel Studies (CFPS), the average house price in 2018 was 767,000 RMB, and the average family income was 87,600 RMB. The clean air policy contributed an estimated added value of about 33,000 RMB, accounting for about 38% of the family income. In addition, in high price-tier cities, the average house price was 1.93 million RMB, with an average family income of 133,100 RMB. Our results indicate that the clean air policy boosted housing values by as much as 96,000 RMB in these cities, constituting over 72% of the average family income. Furthermore, We analyze the dynamic effects of the clean air policy and find the effects are persistent over time after the first year when the policy is implemented.

The rest of this paper is organized as follows. In the next section, we describe our data and present some summary statistics. In Section 3, we present our empirical results, along with a number of potential issues to be addressed. Section 4 conducts a set of robustness checks. In Section 5, we further expand our analysis of the heterogeneous and dynamic effects. Section 6 provides concluding remarks.

2 Data

In this section, we first describe the nature of the clean air policy in China, and then discuss the data used in the study.

2.1 Clean air policy in China

With rapid industrialization and urbanization in China, the consumption of energy increases dramatically, and regional air pollution has become increasingly prominent. In 2013, the State Council promulgated the Air Pollution Prevention and Control Action Plan. The goal of this plan is to drastically reduce air pollution and improve air quality over five years. The main focus areas of the plan are Pearl River Delta, Yangtze River Delta, and Beijing-Tianjin-Hebei. By 2017, it requires that the concentration of inhalable particulate in these areas will be reduced by at least 15%, and the annual average concentration of inhalable particulate in Beijing should be controlled at about 60 micrograms per cubic meter.

Air Pollution Prevention and Control Action Plan is a centrally-planned policy and implemented regionally. Provinces and cities gradually implemented their own clean air policy after the plan's announcement. Table 1 has the years each city implemented the clean air policy. By 2014, 117 cities in a total of 14 provinces have implemented the policy.

The clean air policy contains comprehensive measures, including, for example, remediating small coal-fired boilers and fugitive dust, promoting green and low-carbon transportation, strictly controlling the production of high-energy-consuming and high-polluting industries, advancing green and low-carbon technology innovation, and developing new energy resources. The policy put forward higher and more comprehensive requirements for enterprise pollution control technology and pollution source control. It is committed to reducing air pollution by promoting the upgrading of industrial structure, optimizing energy structure, and improving enterprise innovation. At the same time, the central government includes the achievement of clean air policy goals into the performance metrics of local governments. Zheng and Kahn

(2017) study the development of environmental protection policies in China, and they argue that incentives for local officials are one of the policy tools for the Chinese government to improve air quality. When more environmental goals are included in the performance metrics, the central government can promote or demote local officials based on their performance, which will ultimately motivate local officials to devote more efforts to reducing air pollution.

Table 1: Clean air policy implementation

Year	**Number of cities**	**Cities**
2013	65	Cities in Hebei, Shandong, Shanxi, Zhejiang, Qinghai, and Shaanxi Provinces, Beijing, Tianjin, Shanghai
2014	52	Cities in Jiangsu, Guangdong, Henan, and Xinjiang Provinces, Chongqing

Notes: The clean air policy in China is a five-year plan, it was implemented in 2013 and 2014 across cities. 65 cities and 52 cities implemented the policy in 2013 and 2014 respectively, accounting for 23.21% and 18.57% of all sample cities.

2.2 Data

We use a sample of 280 cities in China from 2003 to 2018 for the study. Housing prices, measured using average urban residential housing prices, are obtained from the Macroeconomic and Real Estate Database of the National Information Center[2].

We obtain 2003-2018 city-level population, economic and infrastructure quality data from the China City Statistical Yearbook[3]. Economic variables include: land prices, GDP per capita, and income. City's infrastructure quality variables include: bus, higher education institute, undergraduate, public library collection, internet service, hospital bed, doctor, and green rate.

We use the consumer price index (CPI) with 2003 as a reference period to calculate the real housing prices, land prices, and income. GDP per capita is adjusted to 2003 RMB, which is deflated using the GDP index. Table 2 shows the descriptive statistics of the variables.

[2] The Macroeconomic and Real Estate Database of the National Information Center, see http://www.crei.cn.

[3] China City Statistical Yearbooks, see https://data.cnki.net/yearbook/Single/N2021050059.

Table 2: Descriptive statistics of variables

Variables	**Measurement method**	**Observation**	**Mean**	**St. Dev**	**Min**	**Max**
Housing prices	Average housing price per square meter (RMB/m^2)	4,480	3,863.34	2,694.61	852.00	16,787.05
Economic variables						
Land prices	Average land price per square meter (RMB/m^2)	4,480	969.28	1,192.83	59.15	7,949.51
GDP per capit	GDP per capital (RMB)	4,480	17,016.26	10,301.80	3,774.66	59,030.24
Income	Per capita disposable income (RMB)	4,480	7,163.73	1,969.41	4,136.28	14,339.07
Population	Population (10,000 people)	4,480	158.32	208.99	21.05	1,467.49
Infrastructure quality variables						
Bus	Number of buses per 10,000 people	4,480	6.66	3.94	0.70	20.51
Higher education institute	Number of higher education institute	4,480	7.81	13.23	0.00	69.00
Undergraduate	Number of undergraduate in regular HEIs	4,480	73,740.99	131,790.30	685.00	721,540.00
Public library collection	Number collections of public libraries per 100 people	4,480	72.95	64.58	3.51	351.34
Internet service	Number of subscribers of internet services (10,000 households)	4,480	61.37	87.78	1.31	533.39
Hospital bed	Number of beds in hospitals per 10,000 people	4,480	58.14	23.78	12.68	130.77
Doctor	Number of licensed doctors per 10,000 people	4,480	28.82	11.93	7.05	74.04
Green rate	Green coverage rate of the built-up area	4,480	0.37	0.07	0.12	0.50

3 Empirical results

Many papers in the literature examine how the clean air policy reduces $PM_{2.5}$ concentrations and improves air quality, which results in better health and fewer mortalities in China (e.g. Cai et al. (2017), Feng et al. (2019), Maji et al. (2020), and Zhang et al. (2019)). We study the effect of the clean air polity on housing prices. Our empirical specification is as follows:

$$ln(Housing\ prices)_{it} = \alpha_0 + \alpha_1 Policy_{it} + \sum_{j=1}^{J} \lambda_j Z_{it,j} + \mu_i + \upsilon_t + \epsilon_{it} \qquad (1)$$

where $(Housing\ prices)_{it}$ is a dependent variable, representing the average urban housing prices of city i in year t. $Policy_{it}$ is a dummy variable, which equals one if city i in year t has implemented clean air policy, and zero otherwise. Z_{it} is a set of control variables, including economic and infrastructure quality variables. μ_i is a set of city dummies and υ_t is a set of year dummies, which control for city and year fixed effects, respectively; ϵ_{it} is a random error item.

We estimate a series of different specifications by gradually increasing the number of control variables in Z_{it} to see the impact of the clean air policy on housing prices. The estimated results are reported in Table 3.

We begin with the simplest specification by only controlling for *Policy*, year and city fixed effects. The result is shown in column (1) of Table 3. The estimated coefficient of *Policy* is statistically significant at 5% level and has a positive effect on housing prices. In column (2) of Table 3, we additionally control for economic variables, and the estimated coefficient of *Policy* remains statistically significant at 5% level and positive. In column (3) of Table 3, we further control for city's infrastructure quality variables, and the estimated coefficient of *Policy* increases to 0.044 and becomes statistically significant at 1% level, which implies that the implementation of clean air policy increases the housing values by 4.4%, holding everything equal. According to the China Family Panel Studies (CFPS) data from 2018, the average house price was 767,000 RMB, and the average family income was 87,600 RMB. Our findings suggest that the clean air policy contributes an added value of 4.4%, equivalent to about 33,000 RMB, which accounts for approximately 38% of the family income.

The estimated coefficients of other variables in column (3) of Table 3 are also as expected. For example, land prices and income of local residents are two important factors affecting house prices. The higher the land price, the higher the housing price; and the higher the income of local residents, the stronger their purchasing power, which leads to higher housing prices. Better medical resources in cities have a positive impact on housing prices. These findings are consistent with Haughwout (1997); Wen and Goodman (2013); Wang and Zhang (2014); Ouyang et al. (2022).

Table 3: Impact of clean air policy on housing prices (baseline regression)

Variables	**(1)**	**(2)**	**(3)**
Policy	0.033**(0.016)	0.041**(0.015)	0.044***(0.015)
Economic variables			
ln(Land prices)		0.040***(0.007)	0.039***(0.007)
ln(GDP per capita)		0.049(0.030)	0.026(0.086)
ln(Income)		0.430***(0.053)	0.441***(0.053)
ln(Population)		0.012(0.041)	0.044(0.036)
Infrastructure quality variables			
ln(Bus)			0.006(0.042)
ln(Higher education institute)			-0.011(0.025)
ln(Undergraduate)			0.008(0.017)
ln(Public library collection)			0.001(0.008)
ln(Internet service)			0.007(0.009)
ln(Hospital bed)			0.049**(0.024)
ln(Doctor)			0.008(0.016)
Green rate			-0.011(0.097)
Constant	7.026***(0.014)	2.616***(0.656)	2.311***(0.662)
Year fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
R-squared	0.097	0.157	0.161
Observations	4,480	4,480	4,480

Notes: Robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

3.1 Potential issues

There are several potential issues that may bias our estimated results. The first issue we identified is the impact of industrial upgrades. If there have been significant changes in the industrial sector during the time period of the study, this could confound our findings, as any observed changes in outcomes might be driven by changes in industrial practices rather than the clean air policy itself. Therefore, we need to ensure that the effects are not being driven by industrial upgrades.

The second issue is the impact of other environmental policies that might have been implemented before or during the time of the clean air policy implementation. These policies could affect the outcomes we are measuring, and if we are unable to control for them, our estimates could be biased. Therefore, we should include other environmental policies as control variables in our model to mitigate their potential impact on our results.

The third issue is the effect of housing and land supply. This is another potential issue that could affect our results. The clean air policy may have an impact on housing and land supply, which could in turn affect housing prices. If this is the case, it implies that our findings are driven by changes in housing and land supply rather than the clean air policy itself. We have looked at the relationship between the clean air policy and housing/land supply and found no such relation.

Overall, our results are robust to the three potential issues. Next, we address each of them in turn.

3.1.1 The impact of industrial upgrades

One may argue that the timing of the clean air policy implemented for cities is not exogenous. Its timing may be coupled with many other major changes that those cities have been experiencing simultaneously. For instance, different cities experience industrial upgrades (from labor-intensive to skill-intensive) at different points of time, and such a structural transition can definitely lead to many outcomes, including the improvement of air quality (due to less polluting activities) and less urgency of implementing the clean air policy, higher housing demand for both quantity and quality, and better quality of amenities (schools, green spaces, etc.) that those high-skilled workers and firms demand. Therefore, the timing of the clean air policy for cities may be related to the process of their industrial upgrades. We indeed find such a relationship. The findings in Table 4 suggest that lower industrial upgrades in fact expedite the policy implementation, holding other things equal.

Table 4: Relationship between industrial upgrades and policy implementation

Variables	**(1)** City implements clean air policy
Industrial upgrades	-1.819**(0.893)
Economic variables	Yes
Infrastructure quality variables	Yes
Constant	Yes
Year fixed effect	Yes
City fixed effect	Yes
Log likelihood	-188.580
Observations	2,800

Notes: We use the data from 2003 to 2012 to conduct logit regression; *industrialupgrades* is measured by the ratio of the tertiary industry output value to secondary industry output value; robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

Since the timing of the clean air policy is related to the process of their industrial upgrades, and if there have been significant changes in the industrial sector during the implementation period of the policy, this could compromise our findings, as any observed changes in housing prices might be driven by changes in industrial upgrades rather than the clean air policy.

To mitigate the impact of the industrial upgrade, we divide our sample into four subgroups, as shown in Table 5. We define alternative treatment groups (i.e., subgroups A and B) and control groups (i.e., subgroups C and D). Then, we compare subgroups A and C, and subgroups B and D, respectively. We report our results in Table 6. The estimation results show that, in both high and low industrial-upgrade cities, the clean air policy boosts housing prices (i.e., 6.3% for the high industrial-upgrade cities and 4.2% for the low industrial-upgrade cities), which reaffirms our findings.

Table 5: Four subgroups of the sample

	High industrial-upgrade	**Low industrial-upgrade**
Implement clean air policy	A(10.35%)	B(31.43%)
Non-implement clean air policy	C(26.79%)	D(31.43%)

Notes: Subgroups A and B include cities that have implemented clean air policy, and subgroups B and C include cities that have not implemented the clean air policy; subgroups A and C are high industrial-upgrade cities, and subgroups B and D are low industrial-upgrade cities; if the industrial-upgrade is above the national average level, the city is defined as high industrial-upgrade, otherwise, it is defined as low industrial-upgrade.

Table 6: The impact of industrial upgrades

Variables	**(1) High industrial-upgrade A&C**	**(2) Low industrial-upgrade B&D**
Policy	0.063***(0.030)	0.042***(0.017)
Economic variables	Yes	Yes
Infrastructure quality variables	Yes	Yes
Constant	Yes	Yes
Year fixed effect	Yes	Yes
City fixed effect	Yes	Yes
R-squared	0.165	0.171
Observations	1,664	2,816

Notes: Robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

3.1.2 Control for other environmental policies

We notice that there are other environmental policies that have been implemented before or during the implementation period of the clean air policy. These environmental policies could also affect housing prices and, if we are unable to control them, our estimates are likely to be biased.

We identify that there are two sets of other environmental policies: the first set of policies that were implemented during the time of the clean air policy include the "Low-Carbon Transportation Construction Pilot Policy" and the "Regional Industrial Green Transformation Pilot Policy"; and the second set of policies that were implemented earlier include the "Acid Rain Control Area" in 1998, the "SO_2 Emissions Trading" in 2002, and the "Carbon Emissions Trading" in 2010. We use the following regression model to control for other environmental policies. It is worth noting that, since the second set of policies was implemented before the time of the clean air policy, we control time with them to capture the dynamic effects of these policies.

$$
\begin{aligned}
ln(Housing\ prices)_{it} = {} & \alpha_0 + \alpha_1 Policy_{it} + \gamma_1 X'_{1it} + \gamma_2 X'_{2i} \times Time_t \\
& + \sum_{j=1}^{J} \lambda_j Z_{it,j} + \mu_i + \upsilon_t + \epsilon_{it}
\end{aligned}
\tag{2}
$$

where the matrix X'_{1it} represents the first set of policies that have been implemented during the study period including the "Low-Carbon Transportation Construction Pilot Policy" and the "Regional Industrial Green Transformation Pilot Policy". X'_{2i} is the second set of policies that were implemented before the study period including the "Acid Rain Control Area", the "SO_2 Emissions Trading", and the "Carbon Emissions Trading". $Time_t$ is used to control for the dynamic effects of the second set of policies.

In Table 7, column (1) reports the estimation results after controlling for other environmental policies implemented during the time of the clean air policy, and column (2) further controls for the second set of policies implemented earlier. The coefficients of *Policy* both remain statistically significant and positive (i.e., 4.1% after controlling for the first set of policies, and 4.8% after controlling for both sets of policies, compared to 4.4% for our baseline result in Table 3), suggesting that our findings remain robust.

Table 7: The impact of other environmental policies

Variables	**(1)**	**(2)**
Policy	0.041***(0.015)	0.048***(0.017)
X_1'	Yes	Yes
$X_2'\times$Time	No	Yes
Economic variables	Yes	Yes
Infrastructure quality variables	Yes	Yes
Constant	Yes	Yes
Year fixed effect	Yes	Yes
City fixed effect	Yes	Yes
R-squared	0.164	0.186
Observations	4,480	4,480

Notes: Robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

3.1.3 Housing and land supply

Another concern is that the clean air policy may lead to a change in housing and land supply, which could affect housing prices. In other words, our results may be driven by changes in housing and land supply induced by the clean air policy rather than the policy itself. Therefore, it is important to look at the relationship between the clean air policy and housing/land supply.

The estimated results in Table 8 show that there are no significant effects of the clean air policy on both housing and land supply, which indicates that our results are unlikely to be driven by the changes in housing and land supply but by the policy itself.

4 Robustness checks

In this section, we conduct a set of robustness checks. The first check is to ensure the parallel trend conditions hold. This refers to the assumption that, in the absence of the clean air policy, the housing prices in treatment and control groups would have followed a similar trend over time. If this assumption is violated, it could bias our estimates of the policy's

Table 8: Impact of the clean air policy on housing supply and land supply

Variables	**(1)** ln(Housing supply)	**(2)** ln(Land supply)
Policy	0.068(0.048)	-0.015(0.053)
Economic variables	Yes	Yes
Infrastructure quality variables	Yes	Yes
Constant	Yes	Yes
Year fixed effect	Yes	Yes
City fixed effect	Yes	Yes
R-squared	0.694	0.388
Observations	4,480	4,200

Notes: Robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

effects. We have compared the trends in housing prices between the treatment and control groups before the policy implementation to confirm that they are similar.

Second, we have also conducted three falsification tests, which are similar to a placebo test. The falsification tests artificially assign the time and city of policy implementation and then estimate its effect on housing prices. If the estimated effects are significantly different from zero, it suggests that our results may be driven by factors other than the clean air policy. These tests help us to ensure that our results are indeed driven by the clean air policy.

Third, our estimations assume the linear impacts of observables on housing prices. If this assumption is invalid, our results may be biased due to functional misspecification. To deal with this potential issue, we have applied the commonly-used propensity score matching (PSM) approach. This technique creates a matched sample of treatment and control units based on similar values on the propensity score, which is the conditional probability of being treated given a set of observed characteristics. This allows us to control for observed differences between the treatment and control groups and to estimate the effects of the policy more precisely.

Finally, it should be noted that land price is one component of housing prices, and the factors affecting land prices also affect housing prices. Therefore, with the endogeneity issue of land prices, our estimates may suffer from a bias. To address this issue, we have adopted the widely-used two-stage least squares (2SLS) model. This model allows us to mitigate the effect of unobserved factors that may be correlated with both the policy and the housing prices, which could otherwise bias our estimates.

We now conduct each of the robustness checks in turn.

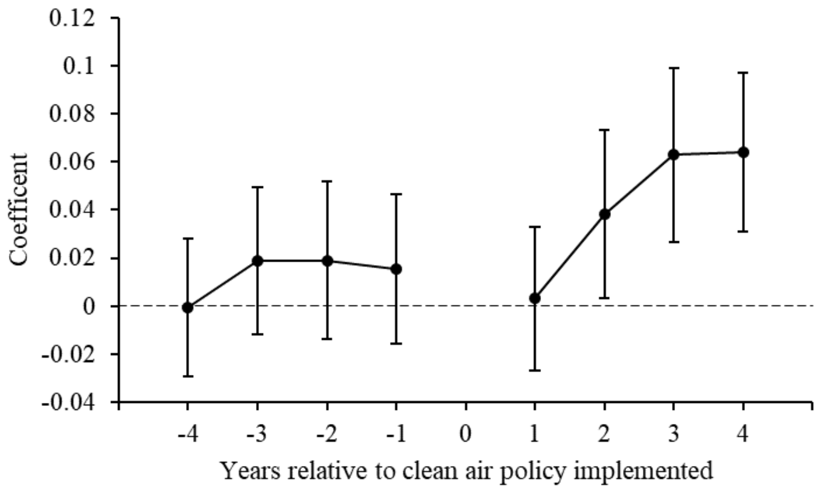
4.1 Parallel trend test

In the absence of a clean air policy, the treatment and control groups ideally should have a similar trend over time. If this condition is violated, it could bias our estimates of the policy's effects. In this section, we conduct the following parallel trend test, which is based on the event study method, to ensure that the trend in housing prices between the treatment and control groups before the policy implementation is similar.

$$\begin{aligned} ln(Housing\ prices)_{it} &= \beta_0 + \beta_{-4} policy_{it}^{-4} + \cdots + \beta_{-1} policy_{it}^{-1} + \beta_1 policy_{it}^{1} + \cdots \\ &+ \beta_4 policy_{it}^{4} + \sum_{j=1}^{J} \lambda_j Z_{it,j} + \mu_i + \upsilon_t + \epsilon_{it} \end{aligned} \tag{3}$$

where $policy_{it}^{'}$ are policy dummy variables, which equal zero, except as follows: $policy_{it}^{-n}$ equals one for cities in the nth year before the clean air policy is implemented, $policyy_{it}^{+n}$ equals one for cities in the nth year after the clean air policy is implemented.

Figure 1 illustrates that before the clean air policy is implemented, there are no significant differences in housing prices between the treatment and control groups. However, the housing prices of the treatment group increase more rapidly than those of the control group in the second year and afterward when the clean air policy is implemented.



Notes: We consider an 8-year window, spanning from 4 years before clean air policy is implemented until 4 years after clean air policy is implemented; the dashed lines represent 95% confidence intervals; we choose the year 0 as the reference group for the model, which represents the current year that clean air policy is implemented.

Figure 1: Parallel trend test

4.2 Falsification tests

In this section, we conduct three falsification tests in which we use fictitious policy events as a falsification strategy. The falsification test artificially assigns the time of policy implementation to a city and then estimates its effect on housing prices, which is similar to a placebo test. A placebo test measures the treatment effect by a false treatment, and it is a controlled experimental method commonly used in medical research (De Craen et al., 1999). For example, to test the therapeutic effect of a drug, patients can be divided into two groups: one group takes the drug, as the treatment group, and the other group takes a placebo (such as a sugar pill), as the control group. During the experiment, patients do not know whether they are taking the drug or a placebo. The placebo test has been widely used in the social science literature since 2009 (Eggers et al., 2021). We use three falsification tests in a similar way to the placebo test. If the estimated effects in our falsification tests are significantly different from zero, it suggests that our results may be driven by factors other than the clean air policy. These three tests help us to ensure that our results are indeed driven by the clean air policy.

The first falsification test is based on La Ferrara et al. (2012). La Ferrara et al. (2012) study the fertility implications of soap operas in Brazil, and they perform a falsification test of artificially moving up the timing of soap operas entry by one year to capture the effects of future entry of soap operas on current fertility. Their hypothesis for this "placebo" experiment is that fertility in places that do not receive soap operas should not be affected by the fact that soap operas may become available in the future. Similarly, Burnett and Kogan (2017) study the impact of road quality on votes, their falsification test uses road quality complaints after the votes as a falsification treatment, i.e. future road quality complaints cannot affect the current votes. We use a similar approach to look at the effects of future policy implementation on housing prices. So, we introduce the $Policy\_future$ variable in Equation (1) to represent future clean air policy implementation. $Policy\_future$ is a dummy variable, which is equal to one if city i in year $t+1$ has implemented clean air policy, and zero otherwise. The coefficient on $Policy\_future$ effectively captures the effect of future policy implementation for cities that do not implement policies in year t. Our hypothesis for this "placebo" experiment is that housing prices in cities that do not implement the clean air policy should not be affected by the fact that clean air policy may be implemented in the future. In other words, policies implemented in the future will not affect current housing prices. We report the results of the first falsification test in column (1) of Table 9. As expected, the coefficient on $Policy\_future$ is not statistically significant.

The second falsification test is based on our arbitrarily "assigning" cities to be treated as cities that implement the clean air policy. La Ferrara et al. (2012) also perform a similar falsification test by fictitious treatment group which exploits information about bordering minimally comparable areas. We artificially assign cities that implement the clean air policy if any of its neighboring cities has implemented the policy. We replace the *Policy* variable with $Policy\_neighboring$ in Equation (1) for our regression. For example, if city i

Table 9: Falsifications 1 and 2

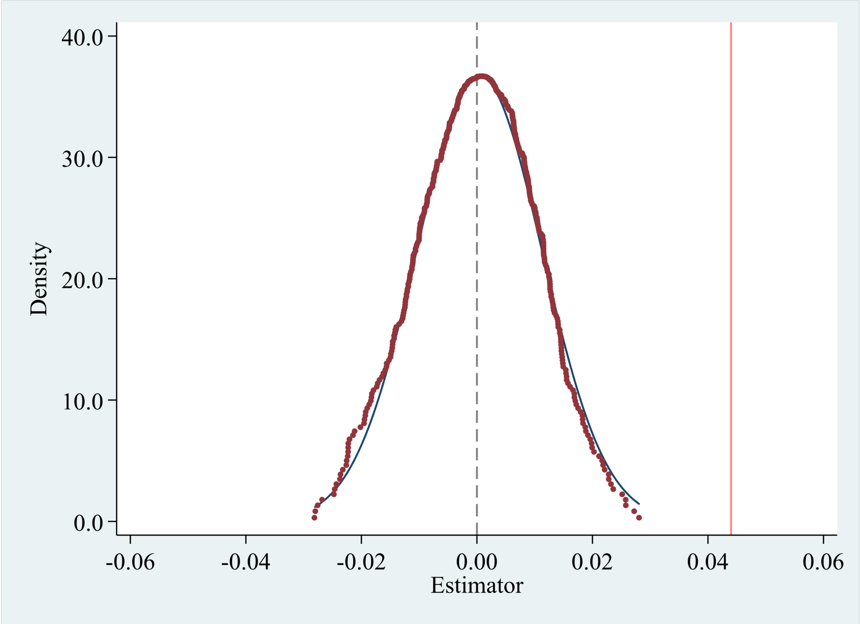
Variables	**(1)**	**(2)**
Policy	0.040***(0.013)	
Policy_future	0.004 (0.015)	
Policy_neighboring		0.007 (0.016)
Economic variables	Yes	Yes
Infrastructure quality variables	Yes	Yes
Constant	Yes	Yes
Year fixed effect	Yes	Yes
City fixed effect	Yes	Yes
R-squared	0.161	0.157
Observations	4,480	4,480

Notes: Robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

does not implement clean air policy in year t, but one of its neighboring cities does, then *Policy_neighboring* of city i in year t equals one. Conversely, if none of its neighboring cities has implemented the policy, then *Policy_neighboring* of city i in year t equals zero. By arbitrarily "assigning" cities to be treated as cities that implement the clean air policy, we should not expect the *Policy_neighboring* variable to be statistically significant. As can be seen in column (2) of Table 9, the coefficient on *Policy_neighboring* is not statistically significant.

Finally, we conduct the third falsification test which is based on a random assignment of the city and year of implementing the clean air policy. This type of falsification test has been widely used in the literature. For example, La Ferrara et al. (2012) generate a random year of soap operas entry to perform a falsification test on the effect of soap operas on fertility in Brazil. Liu and Lu (2015) randomly generate a year of value-added tax pilot reform and randomly select reform sites to fake an experiment on the impact of value-added tax pilot reform on firm investment in China. Agarwal et al. (2017) randomly assign the pseudo-financial profession dummy to people from other professions to fake the impact of financial professionals on mortgage delinquency.

We randomly generate a list of cities implementing clean air policy and generate a random year of implementing the clean air policy for those cities between 2003 and 2018. By doing so, we can construct a "fake" *Policy* variable based on the random assignments of the city and year for policy implementation. We then conduct regressions in Equation (1) using the "fake" *Policy* to replace the actual *Policy* variable. To obtain consistent results, we repeat this random exercise 500 times. We plot the density of the estimated coefficients on "fake" *Policy* in Fig.2. The distribution of these estimated coefficients on "fake" *Policy* is centered around zero (i.e., the mean value is 0.0000704), which is different from our estimate using the actual *Policy* (i.e., 0.044 in column (3) of Table 3). In Table 10, we report the regression coefficients on "fake" *Policy* of first 25 random exercises of 500 random exercises. They are all statistically insignificant and very close to zero. The results of this falsification test reaffirm that our findings are unlikely to be spurious.



Notes: Density of the estimated coefficients from 500 simulations using "false" *policy*; the solid red line on the X-axis represents the actual estimated value (result in column (3) of Table 3).

Figure 2: Placebo city and year of policy

Table 10: Falsifications 3

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Policy	-0.001(0.013)	0.006(0.012)	-0.002(0.009)	0.016(0.011)	-0.003(0.008)
Policy	-0.017(0.010)	0.007(0.012)	0.023(0.010)	-0.014(0.013)	-0.015(0.009)
Policy	0.025(0.012)	-0.021(0.009)	0.002(0.009)	-0.022(0.011)	0.001(0.009)
Policy	-0.003(0.010)	0.005(0.010)	0.011(0.009)	-0.009(0.011)	-0.007(0.011)
Policy	0.007(0.011)	0.005(0.012)	-0.021(0.009)	-0.014(0.011)	0.009(0.013)

Notes: Robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

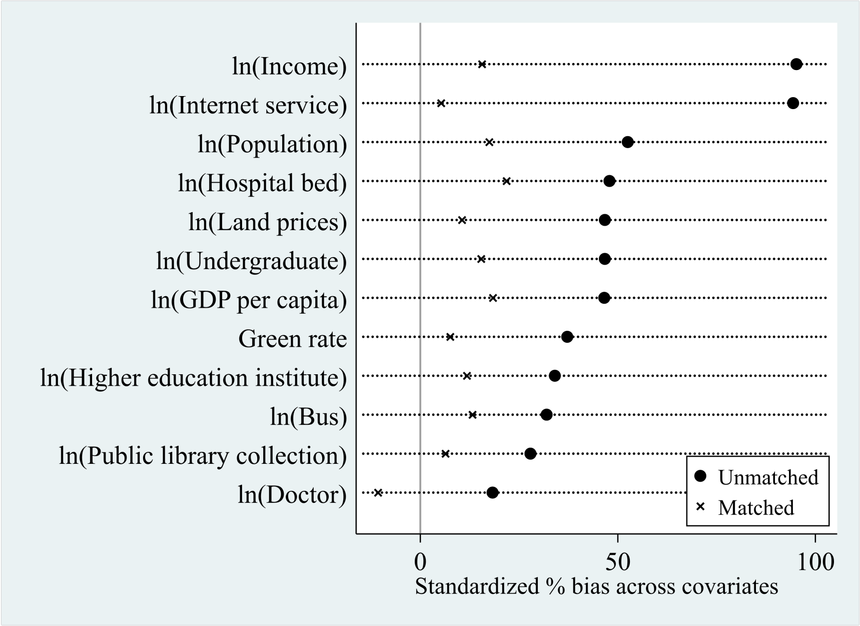
4.3 Propensity score matching

Previous estimations assume the linear impacts of control variables on housing prices. If this assumption is not valid, our estimates may be biased due to function misspecifications. Similar to Lin et al. (2021), we apply the commonly-used propensity score matching (PSM) approach to address this potential issue. This technique creates a matched sample of treatment and control units based on similar values on the propensity score and allows us to control for observed differences between the treatment and control groups and to estimate the effects of the policy more accurately.

Rosenbaum and Rubin (1983) first proposed the concept of PSM. The matching estimation is obtained by simply comparing outcomes among cities implementing the clean air policy (i.e., the treatment group) versus those without (i.e., the comparison group). One advantage of matching estimation (compared to regression) is that the key identifying assumption is weaker: the effect of covariates on the outcome need not be linear, as the matching method estimates the effect by matching cities with the same covariates instead of a linear model for the effect of covariates.

We use kernel matching to determine weights and use a logit model to estimate propensity scores. Fig.3 shows the balance test results for propensity score matching. After matching, the difference for each covariate shrinks substantially, and t-tests for all covariates are not significant. It demonstrates a good quality of the matching for balancing the control group and the treatment group. Furthermore, in order to improve matching quality, only samples with overlapping propensity scores are kept after matching, although doing so will lose sample size. If the common value range of propensity scores is too small, it may lead to a bias. Therefore, we also conduct the test of common support condition, as shown in Fig.4. We can see that majority of the observations fall into region of common support, so there are fewer samples to lose in propensity score matching. In summary, the common support condition of the control and treatment groups is satisfied.

We report the results by using PSM approach in column (1) of Table 11. The coefficient on *Policy* remains similar and significant at 1% level, which reinforces our previous findings[4].



Notes: T-tests for all covariates are not significant after matching, which means there are no significant differences between the mean values of covariates for treatment group and control group.

Figure 3: Balance test

[4] We also use alternative matching methods (k-nearest neighbors matching), and the results are consistent.

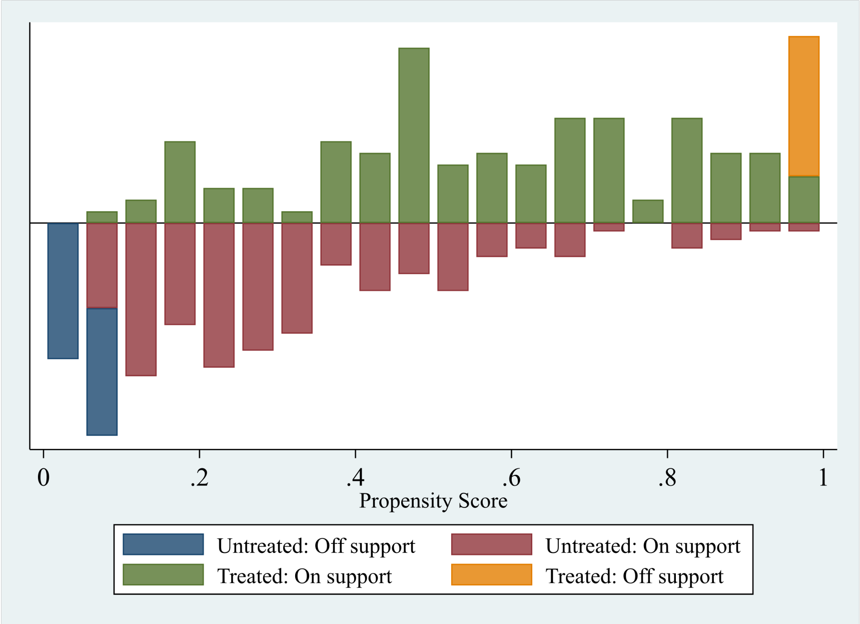


Figure 4: Propensity score distributions of treatment group and control group

Table 11: The results of PSM and 2SLS models

Variables	**(1)** PSM	**(2)** 2SLS
Policy	0.044***(0.016)	0.043***(0.011)
Economic variables	Yes	Yes
Infrastructure quality variables	Yes	Yes
Constant	Yes	Yes
Year fixed effect	Yes	Yes
City fixed effect	Yes	Yes
R-squared	0.180	0.037
Observations	3,808	4,480
F test		21.730
Under identification test		13.701***
Weak identification test		13.648 >8.960

Notes: Robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively.

4.4 Endogeneity issue of land prices

As we know, land prices is one component of housing prices, and the factors affecting land prices also affect housing prices (Wen and Goodman, 2013). One of the concerns is the potential endogeneity issue of land prices. With this issue, our estimates may suffer from a bias. Similar to Johnson et al. (2015), we use the following two-stage regression model to address the issue, which allows us to mitigate the effect of unobserved factors that may be correlated with both the policy and the housing prices:

$$\begin{aligned} ln(Land\ prices)_{it} &= \alpha_0 + \alpha_1 Policy_{it} + \alpha_2 ln(Fiscal\ pressure)_{it} \\ &+ \sum_{j=1}^{J} \lambda_j Z_{it,j} + \mu_i + \upsilon_t + \epsilon_{it} \end{aligned} \tag{4}$$

$$\begin{aligned} ln(Housing\ prices)_{it} &= \alpha_0 + \alpha_1 Policy_{it} + \alpha_2 \overline{ln(Land\ pricess)_{it}} \\ &+ \sum_{j=1}^{J} \lambda_j Z_{it,j} + \mu_i + \upsilon_t + \epsilon_{it} \end{aligned} \tag{5}$$

Equation (4) is the first-stage regression. We add an additional variable $Fiscal\ pressure$ to satisfy the exclusive restriction. The variable $Fiscal\ pressure$ represents fiscal pressure of local governments, measured by fiscal gap (fiscal budget expenditure − fiscal budget revenue). The larger the fiscal gap, the greater the fiscal pressure of local governments. For local governments in China, one of the biggest revenue sources is to sell land, and fiscal pressure will push up the land prices, but should not have a direct effect on housing prices (Wu et al., 2015). Therefore, we use the variable $Fiscal\ pressure$ as an instrumental variable (IV). Equation (5) is the second-stage regression, which uses the $\overline{ln(Land\ prices)}$, predicted from the first-stage regression. The other variables are the same as in Equation (1).

We present the results of two-stage least squares (2SLS) model in column (2) of Table 11. After controlling for the endogeneity of land prices, the estimated coefficient on $Policy$ is 4.3% and statistically significant at 1% level. This result is quite consistent with the baseline regression in Table 3 (i.e. 4.3% vs. 4.4% in column (3) of Table 3). Furthermore, the F test shows its value exceeding 10 and meeting a 1% statistical significance level, and both the under and weak identification tests suggest the effectiveness of the IV. In conclusion, the results of 2SLS model reaffirm our previous finding.

5 Heterogeneous and dynamic effects

In this section, we further examine whether the effect varies across different price-tier cities and changes over time.

5.1 Heterogeneous effects

Housing prices in China vary greatly across cities, and we now examine whether the effect of clean air policy on housing prices differs from low to high price-tier cities. We use a quantile regression for two reasons. First, it can detect whether there exist heterogeneous effects across different price-tier cities. Second, this approach is superior compared to a traditional regression on outlier handling, as it can estimate the conditional median and other conditional quantiles of the dependent variables; in contrast, the traditional regression can only estimate the conditional average. The panel quantile regression model can be expressed as follows:

$$Q_{Y_{it}}(\tau|X_{it}) = \alpha_i + lnX_{it}^T\beta(\tau) + +\mu_i + \upsilon_t + \epsilon_{it}, i = 1, 2, ..., N; t = 1, 2, ..., T \tag{6}$$

where α_i represents the fixed effect, which does not change with the variation in quantile. X_{it} is a set of variables including *Policy*, economic and infrastructure quality variables, which change with the variation of quantile. τ denotes the quantile. In particular, we estimate Equation (6) at the twenty-fifth percentile, median, and seventy-fifth percentile, which represent low price-tier cities, median price-tier cities, and high price-tier cities, respectively.

Table 12 reports the panel quantile regression results, which show the evidence of heterogonous effects across different price-tier cities. The estimated coefficients of *Policy* are all statistically significant at one percent level, but they range greatly from 2% in low price-tier cities, to 3.8% in median price-tier cities, and further to 5% in high price-tier cities. Based on the CFPS data, the average house price in high price-tier cities was 1.93 million RMB in 2018, while the average family income was 133,100 RMB. Our findings indicate that the clean air policy increases the housing value in these cities by 96,000 RMB, which represents over 72% of the family income. Similarly, for the median and low price-tier cities, the clean air policy also contributes significantly to the housing value, accounting for over 26% and 10% of the family income, respectively.

Table 12: Panel quantile regression results

Variables	**(1)** Low price-tier cities	**(2)** Median price-tier cities	**(3)** High price-tier cities
Policy	0.020***(0.004)	0.038***(0.003)	0.050***(0.004)
Economic variables	Yes	Yes	Yes
Infrastructure quality variables	Yes	Yes	Yes
Constant	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
R-squared	0.647	0.679	0.725
Observations	4,480	4,480	4,480

Notes: Robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively; the estimation results of column (1)-(3) correspond to the quantile values of 0.25, 0.5, and 0.75, respectively.

Why is there a much strong effect in high price-tier cities than in low price-tier cities? We offer two possible hypotheses. First, in high price-tier cities, with the rapid economic development, urban residents have become much more affluent, and their desire for clean air has become stronger (Kim et al., 2003; Zheng et al., 2014). Therefore, local residents in those cities are more sensitive to air quality and have a higher willingness to pay for clean air, which leads to a stronger effect in high price-tier cities. At the same time, the improvement of air quality due to the implementation of the clean air policy will further attract more high-income migrants (Chen et al., 2022), which will further boost housing prices. On the other hand, residents are more likely to pursue basic living conditions in low price-tier cities and thus are less sensitive to the surrounding air quality. In other words, we should expect a weak effect in low price-tier cities. Second, clean air policy has cost effect and innovation effect on enterprises. On the one hand, the clean air policy has greatly increased the production cost of regulated enterprises, especially those industrial enterprises with big pollution emissions (Walker, 2011; Curtis, 2018). On the other hand, the clean air policy has incentivized industrial upgrades and technological progress (Bezdek et al., 2008). Compared with low price-tier cities, high price-tier cities have a better economic base and superior technological levels. The implementation of the clean air policy in high price-tier cities should relatively have smaller cost effects, but larger innovation effects, which will ultimately lead to industrial upgrading and expand employment through higher value-added industries and thus further boost local housing prices.

With our current data, unfortunately we can not test these two hypotheses. A meaningful extension for this study is to identify the channels behind these two hypotheses through which the clean air policy may affect housing prices when data is available.

5.2 Dynamic effects

Our baseline regression results reflect the average effect of the clean air policy on housing prices but do not reflect the difference in policy effects over time. We next examine how the effect of the clean air policy on housing prices changes over time.

In Table 13, we report the dynamic effects of the clean air policy on housing prices by using the full sample, low price-tier cities, median price-tier cities, and high price-tier cities. The estimation results in the full sample are shown in column (1) of Table 13. The coefficient of $policy^1$ is negligible and statistically insignificant. However, the coefficients of $policy^2$, $policy^3$ and $policy^4$ are 0.040, 0.064, and 0.064, respectively, and they all are statistically significant at either 1% level or the 5% level. These findings indicate that the effect of the clean air policy on housing prices is only evident after the second year of its implementation.

From cities with different price tiers, the results for low and medium price-tier cities (i.e. columns (2) and (3) of Table 13) are similar to those of the full sample (i.e. column (1) of Table 13). In other words, the policy began to have a significantly positive effect on housing prices only after the second year of the policy implementation. However, in high price-tier cities, all the coefficients of $policies^{1\ to\ 4}$ are statistically significant and much larger than those in low and median price-tier cities, indicating that the effects are much stronger and persistent over time in the high price-tier cities.

Table 13: Dynamic effects of the clean air policy on housing prices

Variables	**(1)** Full sample	**(2)** Low price-tier cities	**(3)** Median price-tier cities	**(4)** High price-tier cities
$policy^1$	0.005(0.013)	0.004(0.007)	0.009(0.011)	0.015**(0.007)
$policy^2$	0.040**(0.016)	0.031***(0.008)	0.041***(0.008)	0.043***(0.006)
$policy^3$	0.064***(0.016)	0.050***(0.007)	0.056***(0.005)	0.083***(0.006)
$policy^4$	0.064***(0.015)	0.026***(0.009)	0.053***(0.006)	0.061***(0.008)
Economic variables	Yes	Yes	Yes	Yes
Infrastructure quality variables	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes
R-squared	0.163	0.647	0.679	0.726
Observations	4,480	4,480	4,480	4,480

Notes: Robust standard errors in parentheses; ***, **, and * are significant at the 1%, 5%, and 10% levels, respectively; $policy^n$ represents the nth year after the implementation of clean air policy; the estimation results of columns (2)-(4) correspond to the quantile values of 0.25, 0.5, and 0.75, respectively.

6 Concluding remarks

Clean air policy is not only an important force to promote green development but also plays an important role in housing prices. In this paper, we study the effect of the clean air policy on housing prices and provide new evidence on how environmental policy may affect housing markets in China. By following a sample of 280 cities over the period of 2003-2018, we find compelling evidence of the positive effect on housing prices: all else being equal, the implementation of the clean air policy boosts housing values by 4.4%. This finding is robust to a series of potential issues and robustness checks. In addition, we further examine whether the effect varies across different price-tier cities and changes over time, and we find strong evidence of such heterogeneous and dynamic effects. In particular, we find that the effect is much strong in high price-tier cities (5%) than median price-tier cities (3.8%) and low price-tier cities (2%). Based on the CFPS data in 2018, we find that the average house prices for high, medium, and low price-tier cities, as well as the national average, are 1,930,000 RMB, 650,000 RMB, 360,000 RMB, and 767,000 RMB, respectively. Our findings indicate that the implementation of the clean air policy has resulted in an increase in housing values by 96,000 RMB, 24,700 RMB, 7,200 RMB, and 33,000 RMB for the high, medium, low price-tier cities, and the nation, representing 72%, 26%, 10%, and 38% of their respective family incomes.

There are quite a few papers in the literature examining the effect of the clean air policy on $PM_{2.5}$ concentrations, air quality, air pollution patterns, health risk, and mortalities in China. Cai et al. (2017) use WRF-CMAQ model system to simulate $PM_{2.5}$ concentrations in Beijing-Tianjin-Hebei region, and they find that clean air policy provides an effective approach to alleviating $PM_{2.5}$ pollution level. Feng et al. (2019) find that clean air policy reduces $PM_{2.5}$ concentration, but increased O_3 concentration, the distribution of pollutants exhibited remarkable spatial heterogeneity. In addition, Maji et al. (2020) find that with the implementation of clean air policy, total deaths due to $PM_{2.5}$ and O_3 decrease. Zhang et al. (2019) use an analytical framework for a cost-benefit analysis estimates the costs and benefits of the implementation of clean air policy, and they find that the public health benefit is 1.5 times the cost of implementation of the clean air policy. This paper differs from them by directly studying the effect of the clean air polity on housing prices. The effect of the clean air policy is multi-faceted, not only directly affecting the environment but also affecting the city's industrial and economic development, as well as the housing market. The formulation of the clean air policy prompts local governments to respond by regulating air pollution activities, reducing industrial emissions, improving transportation, and other measures to improve local air quality. Although the implementation of the policy may increase production costs and reduce production scale in the short run, it will benefit in the long run. A potential extension for this study is to conduct this research at the household level, and to identify channels such as health channels and labor-market channels, through which the clean air policy may impact housing prices.

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