The effect of joint prevention and control plan on atmospheric pollution governance and residents’ willingness to pay

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Received: 30 August 2021 / Accepted: 30 August 2022 / Published online: 11 September 2022
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Abstract
This study investigates the governance effect of China’s joint prevention and control of atmospheric pollution (JPCAP) plan and residents’ willingness to pay for clean air. First, this study delves into the JPCAP plan’s atmospheric pollution governance effect using the difference-in-difference and spatial difference-in-difference models. The results showed that the atmospheric pollution in Beijing–Tianjin–Hebei (BTH) and surrounding cities have significant spatial autocorrelation characteristics. From the autumn and winter of 2017 to 2019, the JPCAP plan implemented by BTH atmospheric pollution transmission channel cities significantly reduced atmospheric pollution. However, the atmospheric pollution governance effect of the JPCAP plan is weaker in 2018–2019 than in 2017–2018. Second, this study introduced the air quality index and three atmospheric pollutants—PM2.5, NO2, and SO2—into the hedonic price model and investigated the residents’ willingness to pay by employing the spatial error model and spatial lag model. Finally, subsample and quantile regression were used to discuss the heterogeneity of residents’ willingness to pay. The results show that the reduction in atmospheric pollution increases residents’ willingness to pay for clean air. Residents have different willingness to pay for reducing different atmospheric pollutants, and there is heterogeneity in willingness to pay across regions and consumption levels. Residents in areas with the JPCAP plan have a higher willingness to pay than those without the JPCAP plan, and there is no spatial autocorrelation characteristic of the willingness to pay of residents in BTH and surrounding cities.

Keywords: Joint prevention and control of atmospheric pollution · Atmospheric pollution governance · Willingness to pay · Spatial econometrics · Hedonic price model
1 Introduction

China’s urbanization, industry, and transportation modernization are altering the country’s atmospheric pollution features. Regional and compound atmospheric pollution problems are becoming increasingly prominent, and atmospheric pollution has noticeable spatial spillover effects (Bao et al., 2015; Jiang et al., 2020; Tian et al., 2018; Wang et al., 2022a; Yan et al., 2018). In the context of China’s administrative vertical management, the current environmental management system with “territorial” characteristics cannot match the air basin boundary of regional and complex atmospheric pollution. Therefore, implementing joint prevention and control of atmospheric pollution (JPCAP) has become an inevitable choice. China’s initial exploration of the JPCAP began in 1998 with the implementation of the acid rain control zone and sulfur dioxide control areas, or “two control zones.” With the realization of the goal of “two control zones,” China has established JPCAP mechanisms in the Beijing–Tianjin–Hebei (BTH), Pearl River Delta (PRD), and Yangtze River Delta (YRD) urban agglomerations. In May 2010, China’s Ministry of Environmental Protection (CMEP) issued the Guideline on Promoting Joint Prevention and Control of Atmospheric Pollution to Improve Regional Air Quality, marking joint prevention and control as the primary means of atmospheric pollution management.

The heavy industry-based industrial structure and coal-based energy structure of Tianjin and Hebei have made BTH the most polluted region in China. Especially in the autumn and winter seasons, unfavorable meteorological conditions for atmospheric pollution dispersion and coal-fired heating in rural areas exacerbate haze pollution. According to CMEP monitoring statistics, the percentage of good air quality days in the BTH region was only 56% in 2016, 22 percentage points below the national average. In the assessment of air quality for 74 Chinese cities, nine of the ten cities with relatively bad air quality are located in this region. During the heating season of 2016, the average concentration of PM$_{2.5}$ in the BTH region was 135 $\mu$g/m$^3$, which was 2.4 times the concentration during the non-heating season. In December alone, there were five large-scale severe haze pollution incidents in this area.

China has accumulated some experience in implementing the JPCAP. The joint control of atmospheric pollution during the Beijing Olympics, Shanghai World Expo, and the two sessions achieved positive results (Shi et al., 2020; Zhang et al., 2016; Zhou & Elder, 2013). In order to more effectively improve the air quality in autumn and winter in the BTH area, CMEP and other departments began to promulgate the Beijing–Tianjin–Hebei and Surrounding Cities’ Action Plan for Comprehensive Treatment of Atmospheric Pollution in Autumn and Winter of 2017–2018 (hereinafter referred to as “2017–2018 JPCAP plan”), which marks the adoption of joint prevention and control mechanisms to combat atmospheric pollution. One of the main goals of the “2017–2018 JPCAP plan” was to reduce the average concentration of PM$_{2.5}$ in atmospheric pollution transmission channel cities (2 + 26) by about 15%, year-on-year, and reduce the number of heavy and above pollution days by about 15%, year-on-year. Moreover, the “2017–2018 JPCAP plan” determines the city scope (“2 + 26” cities) and governance time (from October 2017 to March 2018) of

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1 Notice of Approval by the State Council on Issues Relating to Acid Rain Control Areas and Sulphur Dioxide Pollution Control Areas.

2 In the Beijing-Tianjin-Hebei region, the heating season typically lasts from November through March of the following year.
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Therefore, when the “2017–2018 JPCAP plan” meets the parallel trend hypothesis, it is applicable and convenient to employ the difference-in-difference (DID) model to investigate the atmospheric pollution governance effect since the plan has determined the specific regional scope and implementation time, which provides a ready-made basis for the division of experimental group and control group. The basic idea of the DID model is to treat public policy as a natural experiment and to obtain the net effect by subtracting the change in the outcome variable of the control group from the change in the outcome variable of the experimental group before and after the implementation of the policy. Specifically, (i) divide the entire sample into two groups. One group is affected by the policy, i.e., the experimental group, which refers to “2 + 26” cities in this article. The other group is not affected by the policy, i.e., the control group; (ii) select the outcome variables, which in this article refers to atmospheric pollutants such as PM$_{2.5}$; (iii) perform the first difference between the outcome variables of the experimental group and the control group before and after the implementation of the policy to obtain the changes of the two groups. The heterogeneity of individuals that do not change over time can be eliminated after the first differencing. Then, the second difference is performed on the change quantities of the two groups to eliminate the increment in time variation, and finally, the net effect of the policy is obtained. Therefore, using the DID model can exclude the effects of other environmental policies on atmospheric pollution and better identify the net effect of pollution control of the JPCAP plan.

Although some scholars have studied the governance effect of the “2017–2018 JPCAP plan” (Wang & Zheng, 2019; Zhu & Liao, 2022), there are still some limitations, and further research can be conducted. First, these studies mainly used the DID model for research, which ignored the spatial characteristics of atmospheric pollution in the BTH and surrounding cities. Wang et al. (2019) and Yan et al. (2018) showed that PM$_{2.5}$ in BTH region has a significant spatial spillover effect. Moreover, Fig. 1 shows that during the autumn and winter of 2016–2018, the air quality index (AQI) of “2 + 26” cities has spatial autocorrelation, i.e., high–high and low–low clustering. Figure 1 shows that the atmospheric pollution in Baoding, Shijiazhuang, Hengshui, Xingtai, Handan, and Anyang was the most severe in 2016, and these cities showed the spatial characteristics of high–high.

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Fig. 1 Comparison of air quality index in autumn and winter 2016, 2017, and 2018 in “2 + 26” cities. a Autumn and winter of 2016. b Autumn and winter of 2017. c Autumn and winter of 2018.
clustering. Compared with 2016, the spatial characteristics of high–high clustering were mitigated in 2017 and 2018, but the spatial characteristics of low–low clustering were more prominent. Therefore, the net effect of the JPCAP plan identified by employing the DID model may be biased.

Second, these studies focus on the “2017–2018 JPCAP plan” governance effect but lack research on the JPCAP plan in 2018–2019. According to the “2018–2019 JPCAP plan” issued by CMEP, the atmospheric pollution governance targets have decreased compared to the “2017–2018 JPCAP plan,” with its average PM$_{2.5}$ concentration and the number of days with severe pollution and above decreasing from 15% year-on-year to 3%. It is because the meteorological conditions vary yearly, and CMEP will set the corresponding atmospheric pollution governance targets based on the forecasted meteorological conditions in the fall and winter of that year. When the meteorological conditions are not conducive to pollutant dispersion, the atmospheric pollution governance target set by CMEP will be lowered, as shown in Table 7. Therefore, has the “2018–2019 JPCAP plan” achieved the pollution governance effect under unfavorable meteorological conditions? In which year is the JPCAP plan more effective in atmospheric pollution governance? All these need to be further tested.

Finally, an effective environmental management system requires cooperation between the government, residents, and enterprises. Residents are the subjects of environmental behavior and important participants in environmental governance. For example, burning straw, domestic garbage, and coal-fired heating will aggravate atmospheric pollution. Wang et al. (2019) and Tong et al. (2019) showed that straw burning and coal-fired heating are important factors contributing to atmospheric pollution in autumn and winter in northern China. In addition, residents can exert pressure on polluting enterprises to reduce atmospheric pollution emissions through media exposure and legal action. Therefore, residents’ environmental protection awareness and willingness to pay (WTP) may affect the governance effect of the JPCAP plan. The existing literature studying the residents’ WTP in BTH areas is mainly conducted by the contingent valuation method (CVM), and there is a gap in the literature using the hedonic price method (HPM). Compared with CVM, the result of HPM is more objective and convincing because the result of CVM is greatly influenced by the content of the WTP questionnaire and the scope of the respondents, which may produce a series of biases, such as hypothesis bias, investigator bias, and starting point bias. In addition, due to the spatial autocorrelation of atmospheric pollution in BTH and surrounding cities, the result of WTP estimated by traditional HPM may be biased. In order to make the results more accurate, it is necessary to combine the spatial econometric model and HPM to estimate residents’ WTP. Consequently, the following are the specific research objectives:

To investigate the governance effect of the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan” by employing DID and spatial DID (SDID) model.
To investigate residents’ WTP for clean air in BTH and surrounding cities by combining HPM and spatial econometric models.\(^4\)
To further explore the heterogeneity of residents’ WTP in BTH and surrounding cities.

\(^4\) Since 2017, CMEP has promulgated the JPCAP plan annually. Many studies have shown that restrictions of human activities and traffic caused by the COVID-19 epidemic will affect the air quality. In order to make the results comparable and eliminate the effects of COVID-19 epidemic, this study investigated only the atmospheric pollution governance effect of the JPCAP plan in 2017–2018 and 2018–2019.
There are three main marginal contributions of this study. First, this paper considers the spatial autocorrelation of atmospheric pollution when investigating the governance effect of the JPCAP plan, and the net effect identified by the SDID model is more accurate than the results of existing studies using the DID model. In addition, this paper updates the research data based on the existing studies, and more meaningful conclusions can be drawn by comparing the governance effect of the “2017–2018 JPCAP plan” and the “2018–2019 JPCAP plan.” Second, this study collects hundreds of thousands of second-hand housing transaction records in BTH and surrounding cities and then investigates the residents’ WTP using HPM and spatial econometric models, which fills the research gap. Finally, this paper provides a detailed study of the heterogeneity of residents’ WTP in BTH and surrounding cities. In conclusion, the findings of this paper have strong practical significance and can provide insights to policymakers to further improve the effectiveness of the JPCAP plan in combating atmospheric pollution.

The remaining sections of the article are structured as follows. Section 2 is the literature review, Sect. 3 is the methodology, Sect. 4 is the case study, and Sect. 5 is the discussion. Finally, Sect. 6 contains the conclusion and policy implications.

2 Literature review

China is one of the nations with the most severe levels of atmospheric pollution. People’s physical and mental health is gravely threatened by atmospheric pollution (Gu et al., 2019; Sun et al., 2022), and it has a detrimental influence on economic growth (Xia et al., 2016). In order to solve the problem of atmospheric pollution, China has adopted the regional joint prevention and control mechanism. Residents are the victims of atmospheric pollution and important participants in environmental management. Therefore, this paper conducts a study on the pollution governance effect of JPCAP and residents’ WTP, in an attempt to explore the links between policies, residents, and atmospheric pollution.

2.1 JPCAP atmospheric pollution governance effect

The JPCAP has attracted extensive attention since its adoption and greatly improved air quality (Zhou et al., 2022). Due to the trans-regional transmission characteristics of atmospheric pollution (Chang et al., 2019; Dong et al., 2020; Li et al., 2019; Zhang et al., 2019), compared with the territorial environmental management system, the JPCAP mechanism can solve the problem of the inconsistency between the air basin and the administrative boundary, and has lower atmospheric pollution governance cost and higher efficiency (Wu et al., 2015).

The existing literature has provided a rich investigation of the atmospheric pollution governance effect of JPCAP. In earlier studies, Hao et al. (2000) and Gao et al. (2009) explored the effect of China’s “two control zones” on SO2 pollution control. In 2013, China’s State Council issued the Air Pollution Prevention and Control Action Plan (APPCAP). The governance effect of JPCAP has been studied in terms of the spatial and temporal variation of pollutant concentrations before and after the enactment of APPCAP (Cai et al., 2017; Feng et al., 2019; Maji et al., 2020; Zhang et al., 2018). As meteorological conditions, seasonal changes, and other environmental regulatory policies affect atmospheric pollution, this variation in pollutant concentrations may not be the net governance effect of JPCAP. To better identify the governance effect of JPCAP, some scholars have conducted
studies using causal inference methods. Song et al. (2020) and Wang and Zhao (2021) used the regression discontinuity design (RDD) to investigate the governance effect of JPCAP in the YRD and BTH, respectively. Yang et al. (2016) and Wang et al., (2022a, b) used the DID model to investigate the governance effect of JPCAP in the capital city group of Shandong Province and the key treatment area of APPCAP, respectively. These studies have a potential problem in using the DID model to investigate the governance effect of JPCAP: the division of the experimental and control groups is subjective. In contrast, the “2017–2018 JPCAP plan” defined the city scope (“2+26” cities) and the time (October to March of the following year) of implementation, which provides an objective basis for the division of the experimental group and control group. Therefore, some scholars have used the DID model to study the governance effect of the “2017–2018 JPCAP plan” (Wang & Zheng, 2019; Zhu & Liao, 2022). However, these studies did not consider the spatial spillover effects of atmospheric pollution, which may lead to inaccurate results. Moreover, these studies did not further investigate the governance effect of the “2018–2019 JPCAP plan.” Although Zhang and Cao (2022) considered the spatial characteristics of atmospheric pollution, they only investigated the “2017–2018 JPCAP plan” governance effect. As the meteorological conditions in autumn and winter of 2018–2019 in BTH and surrounding cities are not conducive to the diffusion of pollutants, the atmospheric pollution control effect of the JPCAP plan for 2018–2019 needs further investigation. Thus, this study adopts DID and SDID model to investigate the governance effect of the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan.”

2.2 Residents’ WTP for clean air

The main methods to study WTP are HPM and CVM. The theoretical basis of HPM is the equilibrium theory of market supply and demand proposed by Lancaster in 1966 and the theory of consumer preference proposed by Rosen in 1974. As housing is considered an utterly heterogeneous commodity, the housing price is determined by the utility of all characteristics, such as architectural, neighborhood, and location characteristics. Thus, residents’ WTP for clean air can be calculated by stripping out the characteristic price of the environment from the set of characteristics that affect house prices (Carriazo & Gomez-Mahecha, 2018; Goodman, 1978; Murdoch & Thayer, 1988; Smith & Huang, 1995). With the in-depth study of the implicit price of environmental public goods by HPM, some scholars such as Anselin and Kim considered the spatial autocorrelation of housing prices and combined the spatial econometric model with HPM to enhance the accuracy of estimation (Anselin & Lozano-Gracia, 2008; Brasington & Hite, 2005; Kim et al., 2003; Liu et al., 2020).

Moreover, limited by data availability in China, most scholars have used housing transaction data from one city such as Qingdao, Shanghai, and Beijing to investigate residents’ WTP. The current access to housing microtransaction data in China is limited and mainly comes from three sources: (i) crawling data from real estate agent websites, such as Home Link and Housing World; (ii) obtaining data through field research and interviews; (iii) Obtaining data from real estate data companies or government housing databases. Therefore, scholars have used CVM or air purifier market data to investigate the residents’ WTP in multiple cities (Ito & Zhang, 2020; Pu et al., 2019). CVM investigated WTP by questionnaire (Guo et al., 2014; Sang et al., 2020). Although it is easy to apply and does not require any theoretical assumptions, it also has limitations. The biggest questions are whether the survey accurately simulates the
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The real world and whether the respondents’ answers reflect their true thoughts and behaviors. Therefore, this paper uses second-hand house transaction data and adopts HPM to investigate residents’ WTP in BTH and surrounding cities, which can fill the gap in the current research. The reasons for selecting second-hand housing data in this paper are as follows: First, the housing market in BTH and surrounding cities is shifting from an incremental market to a stock market, and the sample of second-hand housing transaction data is larger. Second, the first-hand housing market is usually controlled by real estate developers, which makes it difficult for the first-hand housing transaction data to fully reflect the supply and demand information of the housing market. In contrast, second-hand housing prices are more determined by negotiations between buyers and sellers and are closer to a competitive market. Finally, the prices of first-hand houses published on the websites of China’s real estate agencies, such as Housing World, are listed prices, not transaction prices, which do not reflect the actual supply and demand situation in the market.

3 Methodology

This section is divided into four parts. First, the data sources, processing methods, and descriptive statistics of variables are presented. Second, the applicability of DID and SDID models are tested and set, respectively. In terms of applicability tests, the main tests are whether the JPCAP plan satisfies the parallel trend hypothesis and whether there is spatial autocorrelation of atmospheric pollution in BTH and surrounding cities. Finally, the applicability of the spatial econometric model is examined and set. In terms of applicability test, it is mainly tested whether there is spatial autocorrelation of second-hand house prices in BTH and surrounding areas. The methodological framework of this paper is shown in Fig. 2.
3.1 Data introduction

This study’s second-hand house transaction data comes from the real estate agent Housing World website. Detailed information about the housing unit sold is included in each transaction record: the date of the transaction, the transaction price, the characteristics of the unit (including architectural characteristics, location characteristics, and neighborhood characteristics), the name of the residential area where the unit is located, and the geographic location of the residential area. Some of the data on housing characteristics, such as floor area ratio, greening rate, and building age, are supplemented by the website of real estate agent 0352 Housing and Leju. The data sample contains 13,341 residential areas, each containing tens or hundreds of housing units. The surrounding facilities of the residential areas, such as schools, banks, restaurants, parks, hospitals, and supermarkets, are obtained from the point-of-interest (POI) data of the Baidu Map API. The data screening and matching methods are as follows. First, the data of housing units with missing housing characteristics are dropped. Second, match the housing price, characteristics, and POI data according to residential neighborhoods’ names and locations.

The data of air quality and atmospheric pollutants are obtained from the website of China Air Quality Online Monitoring and Analysis Platform. In terms of data processing, first, the hourly data of AQI, PM$_{2.5}$, SO$_2$, and NO$_2$ in BTH and surrounding cities from 2016 to 2019 are processed into daily data. In the study of the governance effect of the JPCAP plan, atmospheric pollution data at the prefecture-level city level are used. The specific processing method is as follows:

\[
Pollution = \frac{\sum_{m=1}^{i} pollution_m}{i}
\]

where pollution refers to AQI, PM$_{2.5}$, SO$_2$, and NO$_2$, and is the outcome variable in the DID model. $m$ refers to the city’s air quality monitoring stations, and $i$ represents the number of stations. In the study of residents’ WTP for clean air, atmospheric pollution data at the residential community level are used. According to the inversed distance weight interpolation method proposed by Luechinger (2009), the air quality of a residential neighborhood is obtained by weighting the average of the Euclidean distance between the latitude and longitude of the residential neighborhood and the latitude and longitude of the city air quality monitoring stations. The specific processing method is as follows:

\[
Pollution = \frac{\sum_{m=1}^{i} pollution_m \cdot e^{-3d_m}}{\sum_{m=1}^{i} e^{-3d_m}}
\]

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5 Housing World website: https://www.fang.com, 0352 Housing website: https://www.0352fang.com/3g/, Leju website: https://cs.leju.com.

6 https://www.airstudy.cn/historydata/.

7 Since AQI is the same as atmospheric pollutants such as PM$_{2.5}$, NO$_2$, and SO$_2$, whose higher values indicate poorer air quality, this paper represents the pollution variable as a set of these indicators, but AQI is not an atmospheric pollutant. The Same below.
### Table 1  Classification, definition, and descriptive statistics of variables

| Variable name          | Variable definition                              | Average value | Standard deviation | Minimum value | Maximum value |
|------------------------|--------------------------------------------------|---------------|--------------------|---------------|---------------|
| Housing price          | P                                                | 20,708.67     | 20,217.82          | 1727.00       | 234,216       |
| Pollutants             | AQI                                              | 84.50         | 50.90              | 8.28          | 500.00        |
|                        | PM$_{2.5}$                                       | 53.76         | 44.12              | 17.24         | 693.85        |
|                        | NO$_2$                                           | 35.35         | 17.79              | 12.49         | 176.94        |
|                        | SO$_2$                                           | 20.71         | 23.92              | 8.34          | 680.34        |
| Meteorological factors | wind                                             | 21.03         | 16.02              | 0.00          | 327.66        |
|                        | temperate                                        | 11.95         | 10.86              | -20.50        | 35.30         |
|                        | t*p                                              | 0.10          | 0.29               | 0             | 1             |
| Architectural characteristics | c_time                        | 12.44         | 7.57               | 2.00          | 72.00         |
|                        | g_rate                                           | 0.35          | 0.10               | 0.00          | 0.91          |
|                        | volume                                           | 2.33          | 1.68               | 0.01          | 5.00          |
| Neighborhood characteristics | p_fee                                    | 1.36          | 1.76               | 0.20          | 10.50         |
|                        | market                                           | 2.50          | 1.61               | 0             | 5             |
|                        | bank                                             | 1.66          | 2.24               | 0             | 5             |
|                        | hospital                                         | 2.72          | 1.80               | 0             | 5             |
|                        | l_equip                                          | 1.78          | 1.78               | 0             | 5             |
| Location characteristics | bus                                               | 0.30          | 0.81               | 0             | 5             |
|                        | subway                                           | 2.25          | 1.51               | 0             | 5             |
The meanings of pollution, \( m \), and \( i \) are the same as those in Eq. (1), and \( d_m \) is the Euclidean distance between the residential neighborhood and the monitoring station \( m \). In this study, the optimal parameter value is determined to be three and used \( e^{-3d_m} \) as the distance weight value based on minimizing the root-mean-square prediction error (Chen & Chen, 2012). Finally, the classification, definitions, and descriptive statistics of the variables are shown in Table 1.

### 3.2 DID applicability test and model setting

As the importance of causal inference approaches in policy assessment rises, the DID model is widely used. By differencing experimental and control groups twice before and after policy adoption, the DID model identifies the policy’s net effect. The presumption behind the DID model is that the experimental and control groups must meet the parallel trend hypothesis prior to the policy shock. As shown in Fig. 3, the trends of AQI, PM\(_{2.5}\), and NO\(_2\) in the experimental and control groups are approximately the same before implementing the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan.” Atmospheric pollutants are most severe in autumn and winter (from October to March of the following year) and show a pattern of a rapid increase in October, peaking in December and slowly

![Fig. 3 Trends in air quality index and atmospheric pollution. a Change in AQI from 2016 to 2019. b Change in PM\(_{2.5}\) concentration from 2016 to 2019. c Change in NO\(_2\) concentration from 2016 to 2019. d Change in SO\(_2\) concentration from 2016 to 2019.](image-url)
decreasing after March. In addition, the trends between AQI and PM$_{2.5}$ are highly similar, indicating that PM$_{2.5}$ has the greatest impact on air quality.

To further test whether the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan” meet the parallel trend hypothesis, this study examines whether the differences in AQI, PM$_{2.5}$, NO$_2$, and SO$_2$ between the experimental and control groups are significant in the first eight months and the last four months of JPCAP plan implementation. First, October 2017 and October 2018 are used as the base periods. Second, a series of time dummy variables are generated based on the base period and multiplied with the policy dummy variables as interaction terms. Finally, a two-way fixed model is used to examine the significance of interaction terms before and after the implementation of the JPCAP plan. As shown in Table 8 and Fig. 4, the coefficients of the interaction terms are insignificant before implementing the JPCAP plan and are significant from the second month of the JPCAP plan implementation. Therefore, the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan” satisfy the parallel trend hypothesis. The DID model is specified as follows:

$$\text{Pollution}_{it} = \beta_0 + \beta_1 t_i * p_t + aX_{it} + \gamma_t + \mu_i + \epsilon_{it}$$

(3)

The subscripts $i$ and $t$ denote city and date, respectively, and $pollution_{it}$ represents the set of indicators measuring air quality, which contains AQI and PM$_{2.5}$, NO$_2$, and SO$_2$ pollution. $t_i$ denotes the time dummy variable. $t_i = 0$ indicates before the JPCAP plan implementation, covering October 1, 2016, to September 30, 2017, and April 1, 2018, to September 30, 2018. $t_i = 1$ indicates the JPCAP plan implementation period, covering October 1, 2017, to March 31, 2018, and October 1, 2018, to March 31, 2019. $p_t$ denotes the policy dummy variable. $p_t = 0$ indicates the control group, and $p_t = 1$ indicates the experimental group. The cities of the experimental and control groups are shown in Table 9. $t_i * p_t$ denotes the interaction term of policy and time dummy variables. When the regression coefficient $\beta_1$ is significantly negative, it indicates that the atmospheric pollution control effect of the JPCAP plan is significant. $X_{it}$ denotes the control variables, including wind speed and temperature variables. $\gamma_t$ denotes the time fixed effect, $\mu_i$ denotes the city fixed effect, and $\epsilon_{it}$ denotes the random disturbance term.

### 3.3 SDID applicability test and model setting

Figure 1 shows that the AQI of BTH and surrounding cities has high–high and low–low spatial clustering characteristics. From the results in Table 10, the global Moran’s I of AQI, PM$_{2.5}$, and SO$_2$ are significant at 5% and above levels from 2017 to 2019, which further indicates that there is significant spatial autocorrelation of atmospheric pollution in BTH and surrounding cities. Therefore, this study uses the SDID model further to investigate the governance effect of the JPCAP plan. The SDID model is specified as follows:

$$\text{pollution}_{it} = \beta_0 + \rho W^T \text{pollution}_{it} + \beta_1 t_i * p_t + aX_{it} + \gamma_t + \mu_i + \epsilon_{it}$$

(4)

The difference between model (4) and model (3) is that the $pollution_{it}$ variable in model (4) does not include NO$_2$ pollution because Moran’s I of NO$_2$ pollution insignificant at the 10% level. In addition, a term $\rho W^T \text{pollution}_{it}$ is added to the model (4), which is a spatial lag term representing the local impact of atmospheric pollution from neighboring cities. In this study, the spatial weight matrix $W$ is the rook adjacency matrix, denoted by the dummy variable 1 for cities with common boundaries and 0 otherwise.
Fig. 4 Parallel trend hypothesis test. a AQI (DID_one). b PM$_{2.5}$ (DID_one). c NO$_2$ (DID_one). d SO$_2$ (DID_one). e AQI (DID_two). f PM$_{2.5}$ (DID_two). g NO$_2$ (DID_two). h SO$_2$ (DID_two)
3.4 Spatial econometric models applicability test and setting of HPM

HPM has become a standard and widely used method for studying implicit environmental prices, and the idea behind HPM is to view housing as an utterly differentiated product. Housing prices are composed of the different characteristics that consumers pay to obtain corresponding utility, and the total housing price is the sum of payments for all characteristics. Thus, the housing price reflects the combined WTP for its various characteristics, including environmental quality. Assume that the utility function of the residents is \( U_i(pollution_i, x_i, z_i, M_i, m_i) \) and that the residents satisfy the assumption of utility maximization by purchasing housing, where pollution, is the air pollution level of housing location, \( x_i \) is the vector of architectural characteristics of housing \( i \), \( z_i \) is the vector describing the surrounding conditions, including location and neighborhood characteristics of housing \( i \), \( M_i \) is the housing area, and \( m_i \) is the consumption of resident \( i \) for other expenses besides housing consumption. In addition, the disposable income of resident \( i \) is assumed to be \( y_i \).

Thus, the consumption utility equation for resident \( i \) is as follows (Rosen, 1974):

\[
\max_{pollution, x, z, M, m} U_i(pollution_i, x_i, z_i, M_i, m_i) \\
\text{s.t.} M_i P_i(pollution_i, x_i, z_i, M_i) \leq y_i - m_i
\]  

(5)

Then, a new function is constructed by Lagrange’s method to solve Eq. (5), which is:

\[
\xi = U_i(pollution_i, x_i, z_i, M_i, m_i) - \lambda [M_i P_i(pollution_i, x_i, z_i, M_i) + m_i - y_i]
\]  

(6)

Finally, the partial derivatives of \( pollution_i \) and \( m_i \) are calculated for Eq. (6), and the following equation can be obtained:

\[
\frac{\partial U_i(pollution_i, x_i, z_i, M_i, m_i)}{\partial pollution_i} = \left[ M_i \frac{\partial P_i(pollution_i, x_i, z_i, M)}{\partial pollution_i} \right] \frac{\partial U_i}{\partial m_i}
\]  

(7)

It is generally believed that residents prefer clean air, hence \( \partial U/\partial pollution_i < 0 \), and that residual consumption expenditure \( m_i \) gives positive utility to residents, hence \( \partial U/\partial m_i > 0 \). Therefore, holding the resident’s utility unchanged, the residents’ WTP to reduce the level of atmospheric pollutant around their housing by one unit is the absolute value of \( \partial P_i/\partial pollution_i \).

A potential problem faced in the estimation of \( \partial P/\partial pollution_i \) is choosing the functional form of housing unit price, \( p(\cdot) \). There are three main forms: linear, semi-log, and Box-Cox transformations. Since the linear form is concise and more accurately depicts the WTP of HPM (Smith & Huang, 1995), this paper adopts the linear form.

Moreover, in recent years, house price changes in Chinese cities have shown significant spatial unevenness and are directly influenced by macroeconomics and policies (Li et al., 2017). This spatial heterogeneity is influenced by the quality of urban public goods, such as accessibility around housing (Gu & Zheng, 2010) and the quality of schooling (Davidoff & Leigh, 2008). As shown in Table 11, housing prices in BTH and surrounding cities have significant spatial autocorrelation characteristics. Therefore, this study uses the spatial econometric model to investigate the residents’ WTP.

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8 The reason for keeping the data of 37 cities is that some cities have less housing transaction records on the Housing World website.
3.4.1 Spatial error model (SEM)

The SEM, also known as the spatial autocorrelation model, considers the local effects of the perturbation terms in neighboring areas, i.e., the spatial correlation of house prices is assumed to exist in the random error terms. The model is set up as follows (Anselin & Lozano-Gracia, 2008; Kim et al., 2003):

\[ P_i = \alpha + \beta \cdot \text{pollution}_i + \gamma \cdot x'_i + \delta \cdot z'_i + \eta D' + \epsilon_i \]

\[ \epsilon_i = \lambda W \epsilon + \mu_i, \mu_i \sim N(0, \sigma^2_{\epsilon}) \]  (8)

where \( P_i \) is the price of housing \( i \), pollution \( i \) is atmospheric pollutants around housing \( i \). \( x'_i \) is a vector of architectural characteristics of housing \( i \), including building age, greening rate, and floor area ratio. \( z'_i \) is a vector measuring the location and neighborhood characteristics of housing \( i \), including property management fee, market, bank, hospital, amenity, bus, and subway (Chen & Chen, 2012; Keskin, 2008; Liao & Wang, 2012; Mei et al., 2020; Sun et al., 2016). \( D' \) is the residential fixed effect. \( \epsilon_i \) is the random disturbance term, and \( \lambda \) is a spatial autocorrelation parameter to measure the spatial correlation between the disturbance terms.

3.4.2 Spatial lag model (SLM)

The SLM, also known as the spatial autoregressive model, is concerned with the effect of explained variables in neighboring areas on explained variables in that area, for example, the effects of pollutants and house prices in neighboring cities on the city. The specific model is as follows (Anselin & Lozano-Gracia, 2008; Kim et al., 2003):

\[ P_i = \alpha + \rho W \cdot P_i + \beta \cdot \text{pollution}_i + \gamma \cdot x'_i + \delta \cdot z'_i + \eta D' + \epsilon_i, \epsilon_i \sim N(0, \sigma^2_{\epsilon}) \]  (9)

where \( \rho \) is a spatial autoregressive parameter that measures the degree of spatial interaction between housing prices. The spatial weight \( W \) of SEM and SLM is also the rook adjacency matrix. When the model is SEM, the WTP is \( \left| \frac{\beta}{1 - \rho} \right| \), and when the model is SLM, the WTP is

4 Case study

This section is divided into three parts. First, the results of DID and SDID models to investigate the atmospheric pollution governance effect of the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan” are reported. Second, the results of adopting HPM and spatial econometric models to study the WTP of residents in BTH and surrounding cities are reported. Finally, the results of using subsample and quantile regression methods to explore the heterogeneity of residents’ WTP are reported.
The effect of joint prevention and control plan on atmospheric pollution governance

Table 2 shows the results of investigating the atmospheric pollution governance effect of the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan.” The results in columns (1) to (4) of Table 2 show that the coefficients of \( t^*p \) are significantly negative at the 1% level, which indicates that the JPCAP plan implemented in “2+26” cities is effective in reducing atmospheric pollution. Second, the absolute values of the coefficients of \( t^*p \) in the “2017–2018 JPCAP plan” are greater than those in the “2018–2019 JPCAP plan.” For example, from the results in column (2) of Table 2, it can be seen that the “2017–2018 JPCAP plan” reduced the PM\(_{2.5}\) concentration in “2+26” cities by about 9.25 \( \mu g/m^3 \), and the “2018–2019 JPCAP plan” reduced the PM\(_{2.5}\) concentration in “2+26” cities by about 5.52 \( \mu g/m^3 \).

Moreover, the regression coefficients of \( t^*p \) in columns (2) to (4) of Table 2 show that the net effect of the JPCAP plan on different atmospheric pollutants is heterogeneous. Specifically, the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan” implemented in “2+26” cities reduced PM\(_{2.5}\) by about 9.25 \( \mu g/m^3 \) and 5.52 \( \mu g/m^3 \), NO\(_2\) by about 4.18 \( \mu g/m^3 \) and 2.12 \( \mu g/m^3 \), and SO\(_2\) by about 3.67 \( \mu g/m^3 \) and 1.88 \( \mu g/m^3 \), respectively. Finally, the regression coefficients of wind and temperature variables are significantly negative, indicating that meteorological conditions greatly influence atmospheric pollution, which is consistent with the expectations of this paper.
### Table 3: Spatial difference-in-difference model test results

|                         | AQI                   | PM$_{2.5}$              | SO$_2$                |
|-------------------------|-----------------------|-------------------------|-----------------------|
|                         | Direct                | Indirect | Total     | Direct | Indirect | Total     | Direct | Indirect | Total     |
| **2017–2018**           |                       |                       |                       |
| t*p                    | −8.69***              | −16.73***             | −25.42***             | −6.49***          | −12.34*** | −18.83*** | −2.59*** | −3.21*** | −5.80*** |
| (1.02)                 | (2.05)                | (3.07)                |                       | (0.91)            | (1.79)     | (2.69)     | (0.58)  | (0.73)  | (1.31)    |
| Wind                   | 0.0007                | 0.0010                | 0.0015                | 0.0004            | 0.0008     | 0.0013     | −0.0002 | −0.0002 | −0.0004 |
| (0.0005)               | (0.0010)              | (0.0015)              |                       | (0.0004)          | (0.0008)   | (0.0130)   | (0.0003) | (0.0003) | (0.0006) |
| Temperate              | −0.15***              | −0.28***              | −0.43***              | −0.15***          | −0.28***   | −0.42***   | −0.13*** | −0.16*** | −0.29*** |
| (0.01)                 | (0.03)                | (0.04)                |                       | (0.01)            | (0.02)     | (0.03)     | (0.008)  | (0.010) | (0.017)  |
| ρ                      | 0.714***              | 0.711***              | 0.600***              |
| (0.004)                | (0.004)               |                       |
| Control effects        | Two-way control       |                       |
| **2018–2019**           |                       |                       |                       |
| t*p                    | −5.34***              | −11.02***             | −16.36***             | −4.16***          | −8.59***   | −12.76***  | −1.65*** | −2.35*** | −3.40*** |
| (0.75)                 | (1.56)                | (2.31)                |                       | (0.66)            | (1.37)     | (2.02)     | (0.39)  | (0.56)  | (0.95)    |
| Wind                   | 0.0003                | 0.0006                | 0.0009                | 0.0002            | 0.0003     | 0.0005     | −0.0000 | −0.00011 | −0.00018 |
| (0.0002)               | (0.0005)              | (0.0008)              |                       | (0.0002)          | (0.0005)   | (0.0007)   | (0.0001) | (0.0002) | (0.0003) |
| Temperate              | −0.03***              | −0.06***              | −0.08***              | −0.03***          | −0.05***   | −0.08***   | −0.02*** | −0.03*** | −0.05*** |
| (0.003)                | (0.007)               | (0.010)               |                       | (0.003)           | (0.006)    | (0.009)    | (0.002)  | (0.002) | (0.004)  |
| ρ                      | 0.73 ***              | 0.731 ***             | 0.637 ***             |
| (0.003)                | (0.003)               |                       |
| Control effects        | Two-way control       |                       |

***, **, and * denote statistics significant at the 1%, 5%, and 10% levels, respectively; standard errors are in parentheses.
The results using the SDID model are shown in Table 3. The results in Table 3 show that the spatial autoregressive parameter $\rho$ is significantly positive, confirming that AOI, PM$_{2.5}$, and SO$_2$ have spatial spillover effects. Therefore, it is necessary to employ the SDID model to study the atmospheric pollution control effect of the JPCAP plan. The total effect is divided into three parts: direct effect, indirect effect, and total effect. The regression results in Tables 2 and 3 show that the direct effect estimated by the SDID model differed less from the net effect estimated by the DID model. In addition, the indirect effect is greater than the direct effect, indicating that implementing the JPCAP plan in the surrounding area can reduce local atmospheric pollution. Therefore, the estimation results of the SDID model are more accurate than the DID model. The results of a DID model that does not take into account spatial spillover effects will lead to a downward bias.

4.2 A study of residents’ WTP for clean air

A multicollinearity test is conducted before using the HPM to study residents’ WTP. The results show that the variance inflation factor (VIF) of the variables is less than 10, which indicates that there is no multicollinearity problem. Figure 5 shows the

![Scatterplot of the relationship between air quality index and second-hand housing prices](image-url)
relationship between AQI and the average price of residential neighborhoods in BTH and surrounding cities, suggesting that the residents’ WTP for clean air is about 429.36 yuan/m². After excluding the high housing price data samples of 75 residential neighborhoods, the residents’ WTP decreased to 391.55 yuan/m². Figure 5 only roughly illustrates the relationship between air quality and housing prices. Since housing prices are determined by the utility of housing characteristics, ignoring housing characteristics would create a serious omitted variable problem and leads to biased WTP results. Therefore, it is necessary to use HPM to estimate the residents’ WTP.

Table 4  Results of the hedonic price model

|         | (1)     | (2)     | (3)     |
|---------|---------|---------|---------|
|         | OLS     | SLM     | SEM     |
| AQI     | −249.61*** | −34.25*** | −232.09*** |
|         | (10.22) | (5.99)  | (20.20) |
| c_time  | 575.96*** | 84.15*** | 10.68   |
|         | (20.93) | (11.88) | (13.44) |
| g_rate  | 15,738.10*** | 6596.74*** | 5629.76*** |
|         | (1534.92) | (858.36) | (891.14) |
| volume  | 572.13*** | −71.49   | −160.83*** |
|         | (86.00) | (48.08)  | (48.54) |
| p_fee   | 2977.85*** | 1085.47*** | 898.06*** |
|         | (81.22) | (46.39)  | (47.13) |
| market  | 591.80*** | 239.49*** | 300.38*** |
|         | (109.21) | (61.13)  | (61.18) |
| bank    | 1332.85*** | 180.09*** | 98.35**  |
|         | (68.90) | (39.05)  | (43.24) |
| hospital| 17.14   | 93.11*   | 168.77*** |
|         | (97.85) | (54.70)  | (56.25) |
| l_equip | 1307.80*** | 225.22*** | 138.93*** |
|         | (90.04) | (50.65)  | (51.10) |
| bus     | 8152.86*** | 2519.21*** | 2214.31*** |
|         | (182.49) | (106.86) | (118.83) |
| subway  | 1224.84*** | 341.60*** | 263.45*** |
|         | (119.48) | (66.94)  | (68.52) |
| λ or ρ  | 0.8036*** | 0.8926*** |         |
|         | (0.0054) | (0.0046) |
| Log-likelihood | −137,307 | −130,972 | −131,293 |
| AIC     | 274,638 | 261,969 | 262,611 |
| SC      | 274,727 | 262,066 | 262,700 |
| LM-lag  | 19,674.11*** |         |         |
| Robust LM-lag | 3559.96*** |         |         |
| LM-err  | 84,271.88*** |         |         |
| Robust LM-err | 68,157.73*** |         |         |

***, **, and * denote statistics significant at the 1%, 5%, and 10% levels, respectively; standard errors are in parentheses.
The results of the HPM are shown in Table 4, where columns (1) to (3) show the results of OLS, SLM, and SEM, respectively. The results in column (1) of Table 4 show that architectural characteristic variables such as c_time, g_rate, and volume have a significant positive impact on housing prices; neighborhood characteristics variables such as p_fee, market, bank, hospital, and l_equip have a significant positive impact on housing prices; and location characteristic variables such as bus and subway have a significant positive impact on housing prices. The only contrary to expectation is the sign of the volume variable. The expected sign of the variable is negative because the higher the housing floor area ratio, the lower the comfort level, so the house price and floor area ratio should have an opposite relationship.

The global Moran'I results in Table 11 indicate a significant spatial autocorrelation of housing prices in BTH and surrounding cities. Therefore, the WTP estimated by the OLS model may be biased. In order to more accurately estimate the residents’ WTP, this paper uses SEM and SLM for further investigation. Since LM-lag, LM-error, Robust LM-lag, and Robust LM-error are significant at the 1% level, the log-likelihood of SLM is larger than SEM, and the information criteria AIC and SC are smaller than SEM, and this study concludes that SLM is better than SEM. The estimation results in columns (2) and (3) in Table 4 show that the sign of the coefficient of the volume variable is negative. Therefore, the positive sign of the coefficient of the volume variable in column (1) may be due to the misuse of the OLS model. The results in Table 4 show that the residents’ WTP estimated by the OLS, SLM, and SEM models are 249.61 yuan/m², 174.39 yuan/m², and 232.09 yuan/m², respectively. In addition, the partial elasticity of WTP can be calculated. The partial elasticities of WTP estimated by the OLS, SLM, and SEM models are 1.01%, 0.71%, and 0.95%, respectively.9 Taking the SLM results as an example, when the air quality in the area where the housing is located improves by 1%, the residents’ WTP will increase by 0.71%.

4.3 A discussion on the heterogeneity of residents’ WTP

This section mainly discusses the heterogeneity of residents’ WTP from three aspects. First, differences in residents’ WTP for the reduction in different atmospheric pollutants such as PM$_{2.5}$, NO$_2$, and SO$_2$ are discussed. Second, the differences in residents’ WTP in different cities are investigated, including the JPCAP plan experimental group (20 cities) and the control group (14 cities).10 Finally, the differences in residents’ WTP at different consumption levels are investigated.

As shown in Table 5, the regression coefficients of PM$_{2.5}$, NO$_2$, and SO$_2$ variables are $-35.06$, $-27.64$, and $-267.35$, respectively. According to the above WTP calculation method of SLM, the residents’ WTP for PM$_{2.5}$, NO$_2$, and SO$_2$ reduction is 180.26 yuan/m², 144.79 yuan/m², and 1274.31 yuan/m², respectively. In addition, the partial elasticity of residents’ WTP for reducing PM$_{2.5}$, NO$_2$, and SO$_2$ is 0.47%, 0.25%, and 1.27%%, respectively. From these results, it can be seen that there are large differences in the residents’

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9 The partial elasticity of WTP is calculated as 

$$
\varepsilon = \left( \frac{\partial P}{\partial \text{pollution}} \cdot \frac{\partial (\text{pollution})}{\partial P} \right) = \frac{\text{MWTP} \cdot (\text{pollution})}{\text{P}}
$$

10 Since some cities such as Linfen, Cangzhou, and Anyang have fewer housing transaction records, with only a few dozen second-hand house transaction records, the data samples from these cities are excluded when analyzing the heterogeneity of residents’ WTP in different cities.
Residents have the highest WTP for reducing SO₂ and the lowest WTP for reducing NO₂. Second, Fig. 6a shows that the second-hand housing prices in these 34 cities have a significant spatial autocorrelation. Figure 6b demonstrates the spatial distribution of second-hand housing prices in these 34 cities, showing significant high–high and low–low spatial clustering characteristics. The results show that the WTP of residents in the experimental and control group cities is 534.23 yuan/m² and 31.29 yuan/m², respectively. In addition, the residents’ WTP for the reduction of PM₂.₅, NO₂, and SO₂ in the experimental group cities is 844.09 yuan/m², 702.48 yuan/m², and 1597.30 yuan/m², respectively. The residents’ WTP for reducing PM₂.₅ and SO₂ in the control group cities is 9.37 yuan/m² and 297.31 yuan/m², respectively. The residents’ WTP for the reduction of NO₂ is 123.51 yuan/m², but the sign of this value is positive. These results indicate that residents in the JPCAP plan experimental group cities have higher WTP than the JPCAP plan control group cities.

WTP for the reduction in different atmospheric pollutants in BTH and surrounding cities. Since the SLM model is superior to the SEM model, columns (1) to (3) are the results of SLM model estimation. ***, **, and * denote statistics significant at the 1%, 5%, and 10% levels, respectively; standard errors are in parentheses.

|          | (1)          | (2)          | (3)          |
|----------|--------------|--------------|--------------|
| PM₂.₅    | −35.06***    | (7.80)       |              |
| NO₂      | −27.64***    | (9.75)       |              |
| SO₂      | −267.35***   | (20.20)      |              |
| c_time   | 83.05***     | (11.89)      | 69.44***     |
| g_rate   | 6751.10***   | (858.07)     | 6113.32***   |
| Volume   | −77.34       | (48.10)      | −61.97       |
| p_fee    | 1088.70***   | (46.38)      | 1046.64***   |
| Market   | 241.36***    | (61.16)      | 214.90***    |
| Bank     | 184.05***    | (39.04)      | 188.08***    |
| Hospital | 84.42        | (54.65)      | 68.08        |
| l_equip  | 222.18***    | (50.65)      | 193.67***    |
| Bus      | 2538.44***   | (106.73)     | 2438.58***   |
| Subway   | 335.14***    | (66.94)      | 292.99***    |
| ρ        | 0.8055***    | (0.0053)     | 0.7902***    |

Since the SLM model is superior to the SEM model, columns (1) to (3) are the results of SLM model estimation. ***, **, and * denote statistics significant at the 1%, 5%, and 10% levels, respectively; standard errors are in parentheses.
Moreover, Fig. 7 shows the residents’ WTP in different regions. Figure 7a depicts the scatter plots of the relationship between second-housing prices and AQI for nine different regions in 34 cities, and Fig. 7b shows the spatial distribution of residents’ WTP in these 34 cities. Figure 7a shows that the relationship between AQI and second-housing prices varies considerably in different regions. Taking the three scatter plots in the first horizontal row as an example, the relationship between AQI and second-housing prices in the first and second scatter plots show a negative correlation. The slopes are $-18.05$ and $-1855.19$, respectively, so the residents’ WTP in these two regions are roughly
18.05 yuan/m$^2$ and 1855.19 yuan/m$^2$. The third scatterplot shows a positive correlation between the AQI and housing price, indicating that the worse the air quality around the house, the higher the house price. Figure 7(b) shows no spatial clustering characteristic of residents’ WTP. The global Moran’I is 0.056, and the p-value is 0.262, indicating no spatial spillover effect of residents’ WTP in BTH and surrounding cities.

Finally, columns (1) to (5) of Table 6 show that the regression coefficients of AQI, PM$_{2.5}$, NO$_2$, and SO$_2$ variables are significantly negative at the five quantile levels from 10 to 90%. The absolute values of the regression coefficients keep increasing as the lower quartile levels change to higher quartile levels. For example, at the 10% quantile level, residents’ WTP is only 16.86 yuan/m$^2$; at the 50% quantile level, residents’ WTP increases to 98.49 yuan/m$^2$; and at the 90% quantile level, residents’ WTP reaches 219.02 yuan/m$^2$. In addition, it can be found that at each quartile level, residents have the highest WTP for SO$_2$ reduction and the lowest WTP for NO$_2$ reduction, which is consistent with the results in Table 5.

### 5 Discussion

This study first examines the atmospheric pollution governance effect of the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan” in BTH and surrounding cities. Second, since residents are the subjects of environmental behavior and important environmental management participants, this study investigates the residents’ WTP in BTH and surrounding cities and conducts a series of heterogeneity discussions. The results show that the “2017–2018 JPCAP plan” and “2018–2019 JPCAP plan” implemented in the atmospheric pollution transmission corridor cities of BTH have effectively controlled atmospheric pollution, and the effect of the “2017–2018 JPCAP plan” is greater than that of the “2018–2019 JPCAP plan,” which enriches the current

### Table 6 Quantile regression results of residents’ willingness to pay for the reduction in different atmospheric pollutants

|      | (1)          | (2)          | (3)          | (4)          | (5)          |
|------|--------------|--------------|--------------|--------------|--------------|
|      | $\tau = 0.1$ | $\tau = 0.3$ | $\tau = 0.5$ | $\tau = 0.7$ | $\tau = 0.9$ |
| AQI  | $-16.86^{***}$ | $-57.08^{***}$ | $-98.49^{***}$ | $-142.64^{***}$ | $-219.02^{***}$ |
|      | (3.58)       | (3.40)       | (4.46)       | (5.70)       | (13.54)      |
| PM$_{2.5}$ | $-31.09^{***}$ | $-73.80^{***}$ | $-112.43^{***}$ | $-163.78^{***}$ | $-242.58^{***}$ |
|      | (6.74)       | (5.73)       | (5.89)       | (9.45)       | (17.06)      |
| NO$_2$ | $32.31^{***}$ | $-13.15^{**}$ | $-69.02^{***}$ | $-128.41^{***}$ | $-198.17^{***}$ |
|      | (8.88)       | (5.41)       | (6.25)       | (9.95)       | (23.61)      |
| SO$_2$ | $-139.73^{***}$ | $-289.13^{***}$ | $-418.81^{***}$ | $-505.90^{***}$ | $-705.85^{***}$ |
|      | (14.46)      | (12.77)      | (17.01)      | (15.72)      | (21.65)      |

Architectural characteristics | Yes | Yes | Yes | Yes | Yes |
Neighborhood characteristics | Yes | Yes | Yes | Yes | Yes |
Location characteristics | Yes | Yes | Yes | Yes | Yes |
Residential fixed effects | Yes | Yes | Yes | Yes | Yes |

***, **, and * denote statistics significant at the 1%, 5%, and 10% levels, respectively; standard errors are in parentheses.
research on JPCAP plan (Cai et al., 2017; Feng et al., 2019; Zhang et al., 2018). The meteorological conditions in BTH and surrounding cities in the autumn and winter of 2018–2019 are not conducive to the dispersion of atmospheric pollutants, partly explaining the decline of the JPCAP plan’s effect on atmospheric pollution control. However, it is not further discussed in this study. Therefore, it is necessary to explore the mechanism of the JPCAP plan’s effect on atmospheric pollution control in future studies. In addition, the results of the SDID model show that the indirect effect of the JPCAP plan on atmospheric pollution governance is greater than the direct effect, indicating that implementing the JPCAP plan in neighboring cities can reduce the atmospheric pollution in local cities. Therefore, implementing the JPCAP plan should focus on inter-regional cooperation and strengthen the joint prevention and control mechanism. Local governments should emphasize institutional innovation, break through the environmental regulatory system of territorial management, establish a unified and transparent air quality monitoring network, and strengthen inter-regional information sharing.

Moreover, this study considers the spatial spillover effect of atmospheric pollution, so the estimation results are more accurate than those of existing studies (Song et al., 2020; Wang & Zheng, 2019; Zhu & Liao, 2022). The results show that residents have the highest WTP for S\text{O}_2 reduction and the lowest WTP for N\text{O}_2 reduction. This paper explains the results as follows. First, PM_{2.5} in China has been difficult to solve in recent years, so residents have a strong desire to reduce PM_{2.5}. Second, China’s energy structure is dominated by coal, and S\text{O}_2 pollutants from coal combustion are a major contributor to atmospheric pollution. Furthermore, S\text{O}_2 pollution seriously affects human health and causes damage to soil and buildings, so residents have the highest WTP for S\text{O}_2 reduction. In addition, the results of heterogeneity in residents’ WTP indicate that residents in areas with the JPCAP plan have higher WTP than in areas without the JPCAP plan. It is mainly because the air quality in areas where the JPCAP plan is implemented is worse than in areas where the JPCAP plan is not implemented. The average price of second-hand housing in areas where the JPCAP plan is implemented is 25,817.91 yuan/m\textsuperscript{2}, and that in areas where the JPCAP plan is not implemented is 13,503.18 yuan/m\textsuperscript{2}. As a result, the high spending ability and the strong demand for clean air make residents in areas with the JPCAP plan more willing to pay for clean air.

Finally, the results show that residents’ WTP has no spatial clustering characteristics, and residents with high consumption levels have higher WTP. It is mainly because China is currently in the stage of industrialization and urbanization, and the areas with high housing prices are mainly concentrated in the more economically developed cities. As a byproduct of economic development, air pollution is closely related to housing prices, leading to the paradox that the more polluted an area is, the higher the housing price is likely to be. At this stage, Chinese residents are more concerned about transportation conditions, healthcare, and educational resources around their homes than air quality. As a result, it is challenging to fulfill residents’ desire to “vote with their feet” for housing with better air quality. The cross-regional transmission of atmospheric pollution can affect residents’ WTP because the air quality around housing is uncertain and easily influenced by atmospheric pollution emissions from surrounding cities, which is especially obvious in BTH and surrounding cities.

Buyers of low-cost housing are more focused on the residential attributes of the housing; they purchase housing to meet their basic housing needs, so they are less concerned about the air quality around the housing or are unwilling to spend more
money on housing with better air quality. Residents with higher purchasing power have higher demands on the air quality around their homes. Real estate sellers also consider the air quality around the homes as a selling point. In addition, studies have shown that local governments are less willing to accept polluting plants when threatened with the displacement of wealthy taxpayers. In contrast, local governments are more willing to promote economic development in relatively poor areas by allowing factories to enter (Hanna, 2007). In this way, the price of high-priced housing includes the implicit price of air quality and the opportunity cost of industrial production.

### 6 Conclusion and policy implication

This study shows that the JPCAP plan implemented in BTH atmospheric pollution transmission channel cities has effectively reduced atmospheric pollution. Residents’ WTP for the reduction in different atmospheric pollutants is different. Residents’ WTP in areas where the JPCAP plan is implemented is higher than in areas where the JPCAP plan is not implemented, and residents with high consumption levels have higher WTP for clean air. Therefore, the policy implications of this paper are as follows. First, local governments can levy a real estate tax on highly polluted areas as a special fund for atmospheric pollution governance. Additionally, the government can incentivize residents to participate in ecological protection and improve access to environmental rights litigation to push polluting companies to reduce emissions. As some scholars have found in surveys of Chinese residents’ WTP, many respondents believe that the cost of environmental quality improvements “should be paid by the government and polluters.” Second, since residents who buy high-priced houses enjoy good air quality and have higher WTP for clean air, air quality improvement funds can be collected from such high-income groups for atmospheric pollution governance. Finally, due to the spatial spillover effect of atmospheric pollution, local governments should strengthen cooperation and deepen the inter-regional joint prevention and control mechanism through reasonable industrial layout, relocation, and upgrading between regions.

The study’s limitations should also be acknowledged. For example, this study did not consider the regional migration cost of residents, nor did it further explore the atmospheric pollution governance mechanism of the JPCAP plan. Since Chinese residents are more family and hometown oriented, their migration costs are higher, and ignoring such costs may bias the WTP estimates.

### Appendix

See Tables 7, 8, 9, 10, and 11.
|                        | 2017–2018 autumn/winter atmospheric pollution governance target | 2018–2019 autumn/winter atmospheric pollution governance target | 2019–2020 autumn/winter atmospheric pollution governance target |
|------------------------|---------------------------------------------------------------|---------------------------------------------------------------|---------------------------------------------------------------|
| The average concentration of PM2.5 decreased by about 15% year-on-year | Heavy and above pollution days reduced by about 15% year-on-year | The average concentration of PM2.5 decreased by about 3% year-on-year | Heavy and above pollution days reduced by about 3% year-on-year |
|                        | The average concentration of PM2.5 decreased by about 3% year-on-year | Heavy and above pollution days reduced by about 4% year-on-year | Heavy and above pollution days reduced by about 6% year-on-year |
Table 8 Parallel trend hypothesis test results

|       | (1)     | (2)     | (3)     | (4)     |       | (1)     | (2)     | (3)     | (4)     |
|-------|---------|---------|---------|---------|-------|---------|---------|---------|---------|
|       | AQI     | PM$_{2.5}$ | NO$_2$  | SO$_2$  |       | AQI     | PM$_{2.5}$ | NO$_2$  | SO$_2$  |
| pre_4 | 1.73    | 0.57    | 2.27    | 0.55    | pre_4 | 0.60    | 0.69    | 0.30    | 0.51    |
|       | (0.39)  | (0.15)  | (1.47)  | (0.12)  |       | (0.14)  | (0.19)  | (0.20)  | (0.14)  |
| pre_3 | −0.58   | −0.40   | 2.10    | −2.36   | pre_3 | 1.74    | 0.28    | 0.16    | −0.94   |
|       | (−0.13) | (−0.10) | (1.35)  | (−0.53) |       | (0.41)  | (0.08)  | (0.11)  | (−0.25) |
| pre_2 | −6.87   | −7.64** | −1.49   | −0.93   | pre_2 | −1.76   | −2.51   | 0.49    | −0.38   |
|       | (−1.54) | (−1.97) | (−0.96) | (−0.21) |       | (−0.42) | (−0.69) | (0.33)  | (−0.10) |
| pre_1 | −3.95   | −4.85   | −0.26   | 1.09    | pre_1 | −1.18   | −0.91   | −0.51   | −0.23   |
|       | (−0.89) | (−1.25) | (−0.17) | (0.24)  |       | (−0.28) | (−0.25) | (−0.34) | (−0.06) |
| Current | −5.09   | −4.43   | −1.90   | −2.00   | Current    | −5.99   | −4.76   | −0.87   | 0.85    |
|       | (−1.14) | (−1.14) | (−1.23) | (−0.45) |       | (−1.43) | (−1.32) | (−0.58) | (0.22)  |
| post_1 | −13.91*** | −11.51*** | −5.29*** | −4.37   | post_1    | −10.84*** | −9.19*** | −6.27*** | −3.22   |
|       | (−3.12) | (−2.97) | (−3.42) | (−0.97) |       | (−2.59) | (−2.54) | (−4.17) | (−0.85) |
| post_2 | −14.27*** | −11.49*** | −6.42*** | −3.48   | post_2    | −10.66*** | −8.73*** | −2.85*  | −1.97   |
|       | (−3.20) | (−2.96) | (−4.14) | (−0.78) |       | (−2.55) | (−2.41) | (−1.90) | (−0.52) |
| post_3 | −14.23*** | −11.71*** | −2.04    | −2.83   | post_3    | −9.36*** | −9.76*** | −0.07   | −1.71   |
|       | (−3.19) | (−3.02) | (−1.31) | (−0.63) |       | (−2.24) | (−2.70) | (−0.04) | (−0.45) |
| post_4 | −7.45*  | −6.03    | −1.88   | −1.63   | post_4    | 1.34    | 0.93    | 0.40    | −0.99   |
|       | (−1.67) | (−1.56) | (−1.21) | (−0.36) |       | (0.32)  | (0.26)  | (0.27)  | (−0.26) |

Table 9 Experimental and control group division

| Experimental group | Control group |
|--------------------|---------------|
| Beijing, Tianjin, Hebei Province (Shijiazhuang, Tangshan, Langfang, Baoding, Cangzhou, Hengshui, Xingtai, Handan), Shanxi Province (Taiyuan, Yangquan, Changzhi, Jincheng), Shandong Province (Jinan, Zibo, Dezhou, Binzhou, Heze, Henan Province (Zhengzhou, Kaifeng, Anyang, Hebi, Xinxiang, Jiaozuo, Puyang) | Hebei Province (Qinhuangdao, Zhangjiakou, Chengde), Shanxi Province (Datong, Linfen, Shouzhou, Jinzhong, Yuncheng, Xinzhou, Lviang, Shandong Province (Qingdao, Zaozhuang, Linyi, Yantai, Weifang, Rizhao, Dongying, Tai’an, Weihai), Henan Province (Luoyang, Pingdingshan, Sanmenxia, Xinyang, Zhoukou, Xuchang, Luohu, Nanyang, Shangqiu, Zhumadian) |

The division of experimental and control groups is based on the “Beijing–Tianjin–Hebei and Surrounding Cities’ Action Plan for Comprehensive Treatment of Atmospheric Pollution in Autumn and Winter” (referred to as the JPCAP plan) issued by the Chinese Ministry of Environmental Protection. According to the content of the JPCAP plan, the “2+26” cities in the BTH atmospheric pollution transmission corridor are classified as the experimental group (28 cities), and the remaining cities in Hebei, Shanxi, Henan, and Shandong provinces are classified as the control group (29 cities).
Acknowledgements The authors thank Professor Sun Weizeng of the School of Economics, Central University of Finance and Economics, for his revision comments. The authors thank two anonymous reviewers for their constructive comments. All remaining errors are ours.

Author contributions SZ involved in conceptualization, methodology, data collection, writing—original draft preparation. CY involved in writing—reviewing and editing. All authors read and approved the final manuscript.

Funding This research is funded by the National Natural Science Foundation of China (Funding No. 72174220), a research grant in Humanities and Social Sciences by the Ministry of Education of China (21YJAZH104).

Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Code availability Stata 16.0 SE, Arcgis 10.2

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

Table 10  Results of the global Moran’s I test for atmospheric pollution

| Pollutants | Moran’s I | E(I) | sd     | Z-value | P-value |
|------------|-----------|------|--------|---------|---------|
| 2017 AQI   | 0.125     | −0.0179 | 0.0693 | 2.01    | 0.031*** |
| PM$_{2.5}$ | 0.209     | −0.0179 | 0.0696 | 3.19    | 0.009*** |
| NO$_2$     | 0.070     | −0.0179 | 0.0673 | 1.27    | 0.109   |
| SO$_2$     | 0.287     | −0.0179 | 0.0682 | 4.41    | 0.001*** |
| 2018 AQI   | 0.264     | −0.0179 | 0.0702 | 3.99    | 0.002*** |
| PM$_{2.5}$ | 0.364     | −0.0179 | 0.0698 | 5.45    | 0.001*** |
| NO$_2$     | 0.068     | −0.0179 | 0.0682 | 1.19    | 0.137   |
| SO$_2$     | 0.301     | −0.0179 | 0.0681 | 4.61    | 0.002*** |
| 2019 AQI   | 0.135     | −0.0179 | 0.0688 | 2.22    | 0.022** |
| PM$_{2.5}$ | 0.260     | −0.0179 | 0.0682 | 4.07    | 0.002*** |
| NO$_2$     | 0.032     | −0.0179 | 0.0700 | 0.66    | 0.234   |
| SO$_2$     | 0.361     | −0.0179 | 0.0712 | 5.27    | 0.001*** |

***, **, * denote statistics significant at the 1%, 5%, and 10% levels, respectively

Table 11  Results of the global Moran’s I test for second-hand house prices

| Variables            | Moran’s I | E(I)     | sd     | Z-value | P-value |
|----------------------|-----------|----------|--------|---------|---------|
| Second-hand housing price | 0.846     | −0.0001  | 0.0046 | 184.5060 | 0.001   |

Acknowledgements The authors thank Professor Sun Weizeng of the School of Economics, Central University of Finance and Economics, for his revision comments. The authors thank two anonymous reviewers for their constructive comments. All remaining errors are ours.

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Funding This research is funded by the National Natural Science Foundation of China (Funding No. 72174220), a research grant in Humanities and Social Sciences by the Ministry of Education of China (21YJAZH104).

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Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.
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