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The Impact of the Beijing Winter Olympic Games on Air Quality in the Beijing–Tianjin–Hebei Region: A Quasi-Natural Experiment Study

Qianjin Wu [1], Zusheng Wu [2], Shanshan Li [3,*] and Zichao Chen [3,*]

[1] School of Physical Education, Shandong University, Jinan 250061, China; 202120715@mail.sdu.edu.cn
[2] School of History and Culture, Sichuan University, Chengdu 610065, China; zhusheng@asu.edu
[3] School of Physical Education, Sichuan University, Chengdu 610065, China
* Correspondence: lishanshan@scu.edu.cn (S.L.); chenzichao@scu.edu.cn (Z.C.)

Abstract: Major sporting events, such as the Olympic Games, can harm air quality due to the construction of large stadiums and other sporting facilities, the transportation of athletes and spectators, and the consumption of energy and resources. To successfully host the 2022 Beijing Winter Olympics, the Chinese government has taken measures to improve air quality in the Beijing–Tianjin–Hebei region, such as limiting car use, closing polluting businesses, and increasing clean energy. Whether these measures have effectively improved the air quality in the Beijing–Tianjin–Hebei region and whether they have had a sustained impact are the concerns of this study. In this study, based on air quality statistics for 24 Chinese cities from 2014–2022, including 2592 observations, we investigated the impact of the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region using the difference-in-difference (DID) method. Our empirical findings indicate that the Beijing Winter Olympics significantly impacted the air quality in the Beijing–Tianjin–Hebei region. We observed a 25% reduction in the air quality index (AQI) and a 28% reduction in the levels of $PM_{2.5}$, holding all other factors constant. Trend analysis further suggests that the Beijing Winter Olympics contributed to the region's long-term trend of air quality improvement. We performed a series of robustness tests, all indicating the reliability of our basic conclusions. In addition, the heterogeneity analysis shows a significant effect of the pollution level and the distance from the capital on the effectiveness of air quality improvement, while economic development had no significant impact. Our findings have important implications for policymakers and other stakeholders interested in improving air quality. The significant improvements from the Beijing Winter Olympics suggest that implementing similar initiatives in other regions may also have positive effects.

Keywords: the Beijing Winter Olympic Games; air quality; air quality index; $PM_{2.5}$; differences-in-differences

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1. Introduction

The environmental impact of major sporting events, particularly on air quality, is a significant concern. Major sporting events, such as the 2022 Beijing Olympics, can positively and negatively impact the environment of the host city and its surrounding towns. On the one hand, hosting such events can bring economic benefits [1], enhance the city's image [2], promote urban infrastructure [3], foster sports culture [4], and strengthen social cohesion [5]. On the other hand, hosting such events can also generate environmental pollution, especially atmospheric pollution, due to the construction of large stadiums and other sports facilities, the transportation of athletes and spectators, and the consumption of energy and resources [6,7]. Beijing and its surrounding regions, namely the Beijing–Tianjin–Hebei region, have long suffered from severe air pollution problems, mainly caused by coal burning, industrial emissions, vehicle exhaust, dust storms, and biomass burning [8–10]. Hosting the Winter Olympics may have exacerbated the air pollution problem in this region, as it required the massive construction and renovation of sports venues, transportation infrastructure, accommodation facilities, and other supporting services [11]. Moreover, hosting the Winter Olympics may have also increased the demand for heating, electricity, and transportation during the winter season, which may have further increased the emissions of greenhouse gases and particulate matter [12]. Therefore, the main research question of this study is: what is the impact of hosting the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region? We used a quasi-natural experiment approach based on the DID method to answer this question. We compared the changes in air quality indicators, such as the AQI and $PM_{2.5}$, between the treatment group (Beijing–Tianjin–Hebei) and the control group (other regions) before and after 2016, when Beijing was awarded the right to host the Winter Olympics. This assessment is crucial to understanding the environmental implications of hosting such large-scale events and developing strategies to mitigate their harmful effects.

DID is a commonly used causal inference method that is usually for assessing the effect of a policy or event on a particular outcome [13]. Ashenfelter (1978) first proposed the classical dual-difference estimation model [14], which, relative to the traditional difference-in-differences model, can avoid the policy or event as an explanatory endogeneity problem that exists with policies or events as explanatory variables, i.e., it effectively controls the interaction effects between the explained and explanatory variables. In air quality studies, DID models can be used to assess the impact of measures such as peak air pollution warnings on population health or to evaluate the effectiveness of air pollution control policies [15]. Alari et al. (2020) used a difference-in-difference model and the propensity-score-matching method to assess the impact of peak air pollution warnings and related interventions on premature mortality (PM_{10}) levels in the Paris region [15]. Bel et al. (2015) evaluated the impact of two speed limit policies on air quality in Barcelona, Spain, using a quantile regression approach and a difference-in-differences model [16]. The evaluation of the DID method involves checking the validity of its assumptions, such as the parallel trend test, using graphical or statistical tests [17]. It also consists of conducting sensitivity analyses to test the robustness of the results to different specifications, such as alternative outcome variables and placebo tests [18]. Moreover, it involves performing heterogeneity analyses to examine whether the treatment effects vary across different subgroups or dimensions, such as pollution levels, geographic locations, or economic development levels.

The modern Olympic movement has long recognised the importance of environmental protection. For example, the 27th Sydney Olympics was held under the "Green Olympics" theme and championed ecological conservation as a core value [19]. However, the impact of the modern Olympics on the ecological environment of the host city can be both positive and negative. On the positive side, the modern Olympics can catalyse improving the municipal climate of cities. For instance, during the preparation for the 1988 Seoul Olympics, the organisers developed a comprehensive program of urban landscaping that included street beautification, new or renovated parks, sculptures, and billboard adjustments. These efforts contributed to the Olympics' success and improved residents' quality of life [20]. However, the construction and preparation of Olympic venues can also significantly negatively impact the ecological environment of the host city. A study by Wang et al. (2019) on the environmental security of Beijing's landscape showed that the construction of Olympic venues was one of the significant events affecting the urban ecosystem. Moreover, the impact of the modern Olympics on the environment is not limited to the physical landscape [21]. A study by Konstantaki and Wickens (2010) on the residents and environmental issues of the London Olympics found that while most residents supported hosting the Olympics, they also had concerns about environmental pollution. This suggests that while the modern Olympics can promote environmental protection, addressing ecological issues comprehensively and proactively is crucial [22].

Since 1994, environmental protection has been integrated into sustainable development and the Olympic legacy by the International Olympic Committee (IOC) and national

Olympic organisations [23]. Significant sporting events, such as the Olympic Games, possess the potential to exert a positive influence on air quality in host cities. Numerous studies have investigated this phenomenon, demonstrating the efficacy of pollution control measures implemented during major sporting events. To better understand the impact of these events on air quality, it is essential to examine specific case studies and the actions taken to mitigate pollution. For instance, Chu et al. (2022) analysed air pollution during the Beijing Winter Olympics. Their findings revealed that implementing pollution control strategies, such as restricting industrial emissions and encouraging eco-friendly transportation, substantially improved air quality. This improvement was evident when comparing pollutant concentrations in the Beijing region during the Winter Olympics to those recorded before the event [24]. Liu et al. (2022) examined the air quality improvement during the 2022 Winter Olympics in Beijing. They discovered that control measures, such as aggressive government measures to reduce pollutant gas emissions, had a more significant impact on reducing $PM_{2.5}$ concentrations than meteorological moderation [25]. De La Cruz et al. (2019) evaluated the air quality of the 2016 Summer Olympics in Rio de Janeiro [6]. They showed that levels of air pollutants decreased during and after the games due to the series of emission-reduction measures implemented by the government. In another study, Rich et al. (2012) examined the impact of air pollution levels during the Beijing Olympics on cardiovascular-disease-related markers [26]. They found that concentrations of particulate matter and gaseous pollutants decreased, and soluble P-selectin and von Willebrand factors decreased. These results suggest that significant sporting events can significantly improve air quality with positive health outcomes.

In July 2015, Beijing was awarded the right to host the 2022 Winter Olympics, and Chongli District in Zhangjiakou City was selected as the co-host. Beijing has thus become the only city to have hosted both the Summer and Winter Olympics [27]. According to the Chinese Ministry of Ecology and Environment, from 4 February to 20 February 2022, the average $PM_{2.5}$ concentrations in Beijing and Zhangjiakou were 36 $\mu g/m^3$ and 22 $\mu g/m^3$, a decrease of 56.1% and 50%, respectively, compared to the same period in 2021. During the Winter Olympics, daily air quality compliance was maintained. These significant decreases in $PM_{2.5}$ concentrations resulted from efforts to enhance air quality during the Olympics [28]. Chu et al. (2022) evaluated the concentration of different air pollutants during the Winter Olympics in Beijing and Zhangjiakou. The results showed that the average concentrations of NO_2, CO, PM_{10}, $PM_{2.5}$, and SO_2 decreased by 43.67%, 38.79%, 27.18%, 45.51%, and 13.52%, respectively, compared with those before the Winter Olympics (1 January to 3 February) [24]. Hou et al. (2022) conducted a study characterising the air quality in 44 cities in the Beijing–Tianjin–Hebei region during the Winter Olympics (31 January to 20 February) [29]. The study found that the primary pollutant was $PM_{2.5}$, with an average value of 46 $\mu g/m^3$, a 23.3% decrease compared to the same period in 2021. The study also found that 83.3% of the days had good weather, and there were no heavily polluted days. The results of these studies support the effectiveness of the measures taken to improve air quality during the Winter Olympic Games.

In recent decades, the Beijing–Tianjin–Hebei region has experienced rapid industrialisation and urbanisation, leading to a significant increase in energy consumption. Consequently, industrial exhausts, automobile exhausts, and various harmful gases have been emitted into the atmosphere, causing frequent haze in northern China [30]. To address this issue, the Chinese government dramatically emphasised the environmental management of the Winter Olympic Games competition area and its surrounding region. The government implemented strict actions to prevent and control air pollution. Policies such as the Action Plan for the Prevention and Control of Air Pollution and the Implementation Rules for the Prevention and Control of Air Pollution in Beijing, Tianjin, Hebei, and the Surrounding Areas were formulated and implemented [31]. Implementing these policies involved specific measures such as increasing the simultaneous reducing of multiple pollutants, controlling motor vehicle exhaust pollution, optimising the regional economic layout, promoting the efficient and clean use of conventional energy sources, and strengthening monitoring and early warning infrastructure capacity building. These measures have been crucial in safeguarding air quality, especially during the Winter Olympic Games.

In summary, we believe there are some research gaps in the current literature. First, previous studies have rarely considered the spatial spillover effects on air quality in significant events in cities like the Beijing Winter Olympics. By "spatial spillover effects", we mean the potential impact on air quality in towns near the event city due to increased traffic-, tourist-, and event-related industrial activities. The Winter Olympics not only directly affects the air quality of the host city but may also affect neighbouring cities. Therefore, studying the air quality of the Beijing Winter Olympics in cities in the Beijing–Tianjin–Hebei region is essential. Second, most of the existing studies on the impact of the Olympic Games on air quality have mainly been conducted by comparing the changes in air quality before and after the Games. However, quasi-natural experimental studies are still lacking (in this context, "quasi-natural experimental" designs refer to assigning subjects to treatment and control groups that mimic natural experiments but are not manipulated by re-investigators). In conclusion, to address these research gaps, this study aims to investigate the impact of the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region. We analysed the impact of the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region by considering spatial spillover effects, using a DID model, and employing city-level data to more accurately assess the air quality changes to investigate the impact of the Winter Olympics on the environment. The investigation was conducted retrospectively to provide policymakers and the public with reliable evidence on the potential benefits and challenges of hosting major sporting events.

2. Theoretical Mechanisms and Research Hypotheses

The impact of the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region can be categorised into direct and indirect impacts. Specific construction and industrial production activities primarily cause an immediate effect to facilitate the construction of venues and infrastructure for the Beijing Winter Olympic Games, which can significantly impact air quality [32]. Other factors like traffic, heating, and construction during the Winter Olympics can also affect air quality. For instance, the need for increased public transportation and logistics during the Winter Olympics may lead to traffic congestion and increased emissions, which can harm air quality [33]. Similarly, the increased need for heating during the Winter Olympics may lead to more coal burning and, subsequently, an increase in pollutant emissions.

On the other hand, indirect impacts refer to environmental protection measures and policies implemented during the preparation and hosting of the Winter Olympics on air quality. For example, the government adopted several emission-reduction measures during the preparation for the Winter Olympics, such as using green power sources such as renewable energy and hydrogen fuel [34], constructing green venues using low-carbon materials and technologies [35], and purchasing carbon offsets from projects that reduce greenhouse gas emissions [36]. These measures are expected to decrease pollutant emissions and positively impact air quality. Moreover, measures such as traffic control and enhanced public transportation to reduce vehicle emissions during the Winter Olympics will also help improve air quality.

However, while some studies have identified the impacts of the Beijing Winter Olympics on air quality, the effects are complex, with both direct and indirect mechanisms that can be difficult to capture fully. As such, this study aimed to identify the overall impact of the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region.

We hypothesised that hosting the Beijing Winter Olympics positively impacted air quality in the Beijing–Tianjin–Hebei region, as the indirect effects of the emission reduction measures and policies outweighed the direct impact of the increased construction and transportation activities.

3. Materials and Methods

3.1. Model Selection and Construction

In this study, the DID method was used to analyse the impact of hosting the Winter Olympics on urban air quality, and the constructed model was as follows:

$$Y_{it} = \alpha + \beta_1 Treat_i \times After_t + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In Equation (1), Y_{it} is the air quality indicator of city i in year t, such as the AQI or $PM_{2.5}$. $Treat_i$ is a dummy variable that equals one if city i belongs to the treatment group (Beijing or Tianjin) and is zero otherwise. $After_t$ is a dummy variable that equals one for the years after 2016 and is zero otherwise. We chose 2016 as the event time point because Beijing was awarded the right to host the Beijing Winter Olympics in July 2015, and we assumed that the preparatory work and the policy measures related to the event had a lagged effect on air quality. The interaction term $Treat_i \times After_t$ is the core explanatory variable that captures the DID estimate of the treatment effect on the treated group. It measures the difference in air quality between the treatment and control groups after 2016 relative to the difference before 2016. X_{it} is a vector of the control variables that includes total city GDP, population size, annual fiscal revenue, and fiscal expenditure. μ_i and λ_t are city- and year-fixed effects that control for unobservable constant factors across time or cities. ε_{it} is the error term, α is a continuous term, and γ and β_1 are band estimation coefficients. Furthermore, we used Stata/MP 17.0 as the software for our DID estimation and other calculations.

Since both air quality pollution and treatment effects have unavoidable spillover [37], this study considered the 14 cities in the Beijing–Tianjin–Hebei region (Beijing, Zhangjiakou, Tianjin, Baoding, Chengde, Anyang, Cangzhou, Handan, Hengshui, Langfang, Qinhuangdao, Shijiazhuang, Xingtai, and Tangshan) as the treated group. These cities were expected to be affected by large-scale pollution or air quality improvements resulting from the treatment measures. Regarding the selection of the control group, since air quality is again similar between spatially adjacent cities [38], cities with the same climate as the cities in the treated group were selected as the control group. Precisely, the control group consisted of Taiyuan, Lvliang, Xinzhou, Linfen, and Yuncheng in Shanxi Province, Yulin, Xi'an, Yan'an, Weinan, Shangluo, Tongchuan, Ankang, and Xianyang in Shaanxi Province, and Qingyang in the Ningxia Hui Autonomous Region. Figure 1 shows the location of these cities.

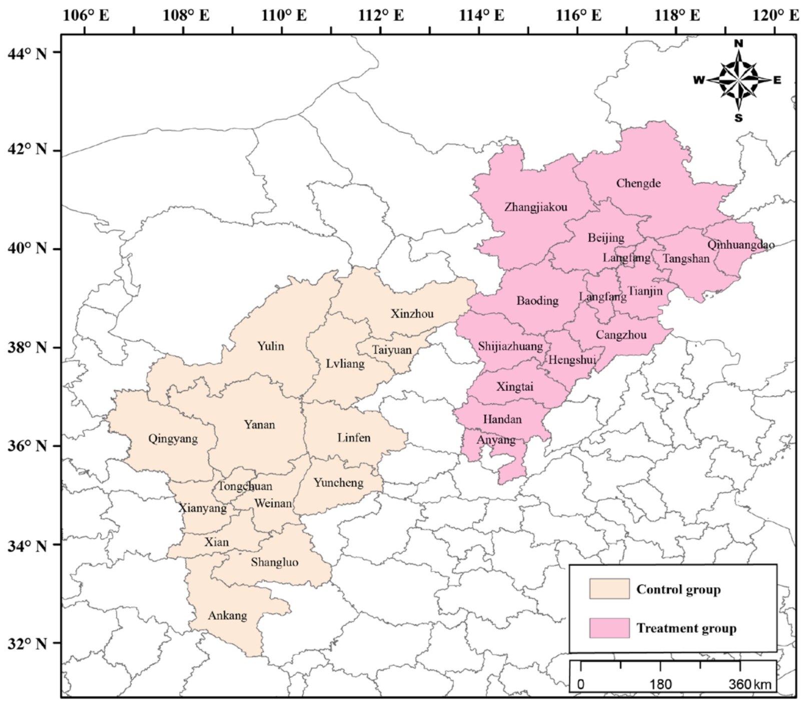


Figure 1. Location of the treated and control groups. Maps were produced by ArcMap 10.8.0 [39].

3.2. Variable Settings

This section describes the selection of the explained, explanatory, and control variables. The main variables and related descriptions are presented in Table 1.

Table 1. Main variables and the associated definitions.

Type of Variable	Variable	Description
Explained variables	Ln (AQI) Ln ($PM_{2.5}$) Ln (PM_{10}) Ln (NO_2)	The logarithm of the AQI, $PM_{2.5}$, PM_{10}, and NO_2, which measure air pollution in each city, was used.
Explanatory variable	$Treat_i \times After_t$	The value of $Treat_i$ and $After_t$ determined the variable value.
Control variables	Ln (GDP) Ln (Pop) Ln (Rev) Ln (Exp)	The logarithm of each city's GDP, population size, fiscal revenue, and fiscal expenditure was used.

3.2.1. Explained Variable

The explained variables in this study were the AQI, $PM_{2.5}$, PM_{10}, and NO_2 for the 28 cities selected from 2014–2022 to assess the impact of the Beijing Winter Olympics on the urban air quality in the Beijing–Tianjin–Hebei region. The AQI is a dimensionless comprehensive index that describes air quality conditions, and its values range from 0 to 500. The AQI is calculated from the concentrations of NO_2, SO_2, CO, $PM_{2.5}$, PM_{10}, O_3, and other pollutants in the air and can provide a quantitative description of the air pollution level from a macroscopic perspective. The larger the AQI value, the more serious the air pollution is [40].

$PM_{2.5}$ is particulate matter in ambient air with an aerodynamic diameter of less than or equal to 2.5 μm [41]. The primary sources of $PM_{2.5}$ are anthropogenic emissions, mainly the combustion of fossil fuels, straw, garbage, and other substances [42]. These tiny particles attach to pollutants like sulfides, nitrogen oxides, and heavy metal particles, which can cause respiratory diseases such as pulmonary sclerosis and bronchitis when they penetrate the human respiratory tract [43].

PM_{10} is a gaseous air pollutant composed of particles with a diameter of 10 micrometres or less [44]. It is mainly derived from the incomplete combustion of hydrocarbons such as coal, wood, diesel, and crop waste, as well as sea salt, pollen, and dust from unsealed roads [45]. PM_{10} can also irritate the eyes and throat, exacerbate asthma and heart disease symptoms, and increase the risk of some types of cancer [44].

NO_2 is a greenhouse gas essential to forming ozone [46]. Anthropogenic NO_2 is mainly released from high-temperature combustion processes, such as motor vehicle exhaust and boiler exhaust emissions, and NO_2 is also one of the causes of acid rain [47]. Moreover, it can cause health problems such as cardiovascular disease, nervous system damage, and enzyme inhibition [48].

We used the natural logarithms of the AQI, $PM_{2.5}$, $NO_{2,}$ and PM_{10} (Ln(AQI), Ln($PM_{2.5}$), Ln(NO_2), and Ln(PM_{10})) as our explained variables because they have skewed distributions and taking the logarithm reduces heteroskedasticity and improves the normality of the error term [49].

3.2.2. Explanatory Variable

The core explanatory variable of this paper was the interaction term $Treat_i \times After_t$, which captures the DID estimate of the treatment effect on the treated group. It was used to measure the difference in the air quality between the treatment group (Beijing–Tianjin–Hebei) and the control group (other regions) after 2016, relative to the difference before 2016.

3.2.3. Control Variable

To assess the impact of hosting the Winter Olympics on urban air quality, we selected several control variables in this study, including urban GDP, population size, revenue, and fiscal expenditure.

Urban GDP is a commonly used measure of a city's economic volume and growth, and it is defined as the sum of the market value of all final goods and services produced in a certain period. The environmental Kuznets curve describes the relationship between urban GDP and air quality, suggesting that economic growth may worsen air quality due to increased industrial and transportation activities and emissions. However, it may improve air quality due to increased environmental awareness, government efforts, and technological innovations [50].

Urban population size is a typical indicator of urbanisation and reflects the level of social and economic activities. An increase in urban population size may positively and negatively affect air quality. On the one hand, it may lead to increased human activities such as industry, transportation, and construction, which generate more pollutants and exhaust gases. On the other hand, it may also imply a higher level of urban economic development, which promotes environmental management technology and governance [51].

Urban fiscal revenue is the total financial income that urban governments obtain through taxation, fees, and operating state-owned assets in a certain period. The impact of urban fiscal revenue on air quality can also be positive or negative. Some studies have shown that increased city revenues can improve air quality, as more resources can be used for environmental protection and management, such as promoting clean energy and building wastewater treatment facilities [52]. However, other studies have argued that urban economic development and industrial expansion may increase pollution emissions and environmental pressures, which can offset the positive effects of urban fiscal revenues on air quality improvement [53].

Urban fiscal expenditures refer to the capital expenditures of urban governments for public services, infrastructure construction, and social security. The impact of urban fiscal spending on air quality can be positive and negative. Urban fiscal expenditures may be spent on environmental protection facilities and pollution control, positively affecting air quality. However, urban fiscal expenditures may also increase economic activities, thus exacerbating environmental pollution and negatively affecting air quality [53].

Urban GDP, population size, revenue, and fiscal expenditure can positively and negatively impact air quality. While increased economic growth and urbanisation can lead to higher emissions and pollution, they can also promote environmental protection efforts and improved management. We used the natural logarithms of urban GDP, urban population, urban fiscal revenue, and urban fiscal expenditures (Ln(GDP), Ln (Pop), Ln (Rev), and Ln (Exp)) as our control variables. These variables also have a skewed distribution, and taking the logarithm can reduce the scale differences and improve the comparability across cities [54].

3.3. Data Source

The air quality data involved in this study were obtained from the China Air Quality Online Monitoring and Analysis Platform (https://www.aqistudy.cn/ (accessed on 29 April 2023)), which provided daily and monthly data for the 28 cities containing the experimental and control groups from January 2014 to December 2022. The platform collects data from the China National Environmental Monitoring Center (http://www.cnemc.cn/sssj/ (accessed on 29 April 2023)), which monitors the concentrations of NO_2, SO_2, CO, $PM_{2.5}$, PM_{10}, O_3, and other pollutants in the air and calculates the AQI based on a standard formula. The sample cities' GDP, government expenditures, fiscal revenue, and population numbers for the years 2014 to 2022 were obtained from the National Bureau of Statistics of the People's Republic of China (http://www.stats.gov.cn/ (accessed on 29 April 2023)), which publishes annual statistical reports and bulletins for various economic and social indicators at the national, provincial, and city levels. The original dataset had 2592 observations for air quality variables (AQI, $PM_{2.5}$, NO_2, SO_2) and 252 observations for economic and demographic variables (GDP, population, revenue, expenditure). To implement these data into Equation (1), the annual average values of the air quality variables and the yearly socioeconomic data were matched for each city and year. Missing data were addressed using interpolation techniques in SPSS 26 [55] to estimate values for missing air quality or socioeconomic data points. The descriptive statistics of the variables are shown in Table 2.

Table 2. Descriptive statistics.

	Control Group				Treatment Group			
Variables	**Observation**	**Mean**	**Min**	**Max**	**Observation**	**Mean**	**Min**	**Max**
AQI	1296	89.52 (30.93)	34	303	1296	100.46 (35.15)	42	301
$PM_{2.5}$ (24 h average μg/m^3)	1296	47.57 (29.08)	10	206	1296	56.64 (35.56)	11	276
PM_{10} (24 h average μg/m^3)	1296	87.39 (26.44)	40	157	1296	102.38 (38.28)	39	224.33
$N0_2$ (24 h average μg/m^3)	1296	35.12 (13.77)	8	83	1296	38.27 (16.03)	10	96
GDP (RMB hundred million)	126	2154.71 (2133.41)	266.41	11,486.51	126	6114.54 (8416.35)	1139.00	41,610.90
Population (ten thousand people)	126	396.40 (247.83)	69.83	1299.59	126	825.98 (489.75)	300.18	2195.40
Revenue (RMB hundred million)	126	177.65 (196.36)	20.06	926.80	126	1306.06 (2921.16)	100.29	14,347.21
Expenditure (RMB hundred million)	126	420.33 (264.06)	83.01	1573.13	126	1581.74 (3198.68)	15.01	16,335.90

Note: standard errors are in parentheses.

4. Empirical Results

4.1. Main Results

Since the AQI and $PM_{2.5}$ levels are often used as air quality indicators, we examined the impact of hosting the Beijing Winter Olympics on these two indicators separately. We used four different regression models based on Equation (1) to estimate the DID effect of the event on the air quality in the Beijing–Tianjin–Hebei region. Model (1) used Ln(AQI) as the explained variable and only included the dummy variables ($Treat_i \times After_t$) as explanatory variables. Model (2) used Ln($PM_{2.5}$) as the explained variable and only included the dummy variables as explanatory variables. Model (3) used Ln(AQI) as the explained variable and included both the dummy variables and the control variables (Ln(GDP), Ln(Pop), Ln(Rev), Ln(Exp)) as explanatory variables. Model (4) used Ln($PM_{2.5}$) as the explained variable and included the dummy and control variables as explanatory variables. Table 3 presents the regression coefficients and standard errors of the four models. The results showed a consistent and significant negative effect of hosting the Beijing Winter Olympics on air quality improvement, with or without considering the control variables. The negative regression coefficients for both indicators were significant at the 1% level, indicating that hosting the Winter Olympics positively impacted air quality in the region, regardless of the model specification or the inclusion of control variables. Specifically, according to models (1) and (3), holding the Winter Olympics reduced the AQI by about 25%, holding all other factors constant; models (2) and (4) reduced $PM_{2.5}$ levels by about 29% and 28%, respectively. Percentage changes in the AQI and $PM_{2.5}$ levels were obtained by exponentiating their logarithmic coefficients and multiplying by 100. Furthermore, the regression results with control variables suggested that hosting the Winter Olympics positively affected population growth and negatively affected fiscal expenditure in the Beijing–Tianjin–Hebei region. However, the effect on regional GDP growth and fiscal revenue was insignificant.

Table 3. Regression coefficients of DID estimation for air quality indicators.

Variables	Ln (AQI)	Ln ($PM_{2.5}$)	Ln (AQI)	Ln ($PM_{2.5}$)
Model	(1)	(2)	(3)	(4)
$Treat_i \times After_t$	−0.287 *** (0.065)	−0.339 *** (0.106)	−0.287 *** (0.067)	−0.332 *** (0.096)
Ln (GDP)			0.001 (0.056)	0.019 (0.079)
Ln (Pop)			0.314 *** (0.043)	0.555 *** (0.064)
Ln (Rev)			0.060 * (0.031)	0.021 (0.044)
Ln (Exp)			−0.232 *** (0.053)	−0.343 *** (0.072)
Constant	4.424 *** (0.040)	3.932 *** (0.066)	3.620 *** (0.194)	2.390 *** (0.313)
Year effects	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes
Observations	252	252	252	252
R-squared	0.189	0.219	0.482	0.509

Note: standard errors are in parentheses. *** $p < 0.01$, * $p < 0.1$.

4.2. Robustness Tests

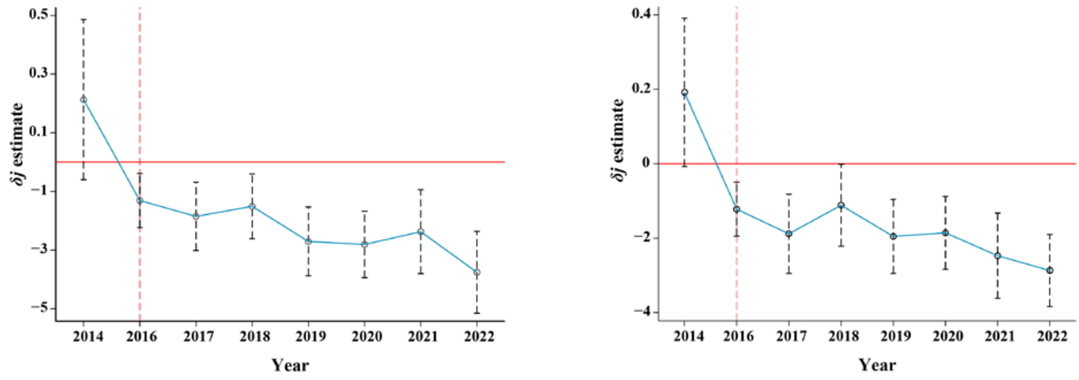
4.2.1. Parallel Trend Test

Our baseline regression results showed the impact of the Beijing Winter Olympics on the air quality in the region, but they did not reflect the differences in this impact over time. Therefore, we referred to the event study method proposed by Jacobson et al. (1993) [56] to test the dynamic effects of the Winter Olympics and constructed the following regression equation to perform a standard trend test:

$$Y_{it} = \alpha + \sum_{j=2014}^{2022} \delta_j Treat_i \times After_t + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

In Equation (2), δ_j denotes the estimated value from 2014 to 2022. The other variables are defined similarly to Equation (1). Figure 2 shows the results of the parallel trend test, which is a graphical way to check the validity of the DID method. The vertical axis shows the difference in Ln(AQI) or Ln($PM_{2.5}$) between the treatment and control groups relative to 2015 with a 95% confidence interval. The horizontal axis shows the year. The dashed vertical line indicates the event time point (2016). The parallel trend test was used to compare the trends in the outcome variables (Ln(AQI) and Ln($PM_{2.5}$)) between the treatment and control groups before and after the event time point (2016). If the trends are parallel before the event, the treatment and control groups are comparable, and there is no confounding factor that affects the outcome variables differently across groups. If the trends diverge after the event, the treatment has a causal effect on the outcome variables.

Using the year before the event (2015) as the base year, Figure 2 plots the estimated coefficients of δj with a 95% confidence interval, which measures the difference in the outcome variables between the treatment and control groups for each year relative to 2015. Figure 2a,b show the dynamic effects of hosting the Beijing Winter Olympics on Ln(AQI) and Ln($PM_{2.5}$) in the host site and its surrounding cities, respectively. As can be seen from the figures, there was no significant difference between the treatment and control groups before hosting the Beijing Winter Olympics, and the parallel trend assumption holds. After entering the preparation period for the Winter Olympic Games, the Ln(AQI) and Ln($PM_{2.5}$) concentrations decreased significantly in the treatment group compared to the control group, which indicates that hosting the 2022 Beijing Winter Olympic Games had a sustained and significant effect on improving the air quality in the Beijing–Tianjin–Hebei region.

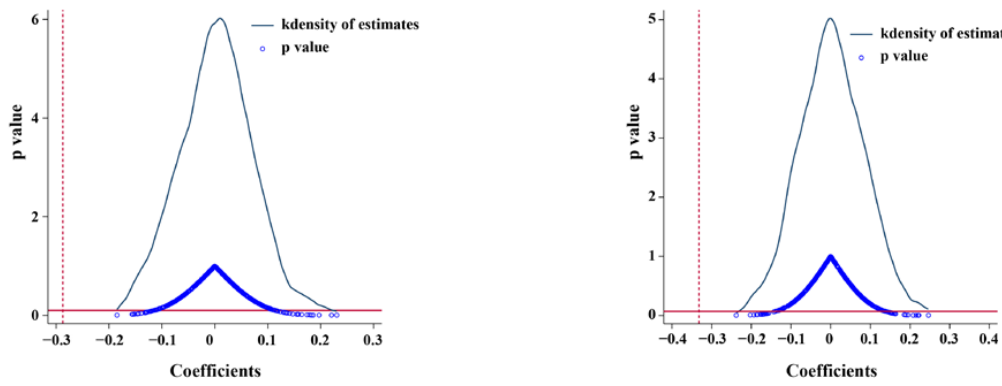


(**a**) (**b**)

Figure 2. The results of the parallel trend test for Ln(AQI) and Ln($PM_{2.5}$). (**a**) The parallel trend test for Ln(AQI); (**b**) the parallel trend test for Ln($PM_{2.5}$). The figure was produced by Stata/MP 17.0 [57].

4.2.2. Placebo Test

The baseline regression analysis showed a significant improvement in the air quality during the Olympics. To test the robustness of our results, we conducted a placebo test using random assignment [58]. We randomly selected 14 cities out of the 28 to be the treated group, while the rest were the control group. We then performed a baseline regression using Equation (1) and conducted 500 simulations. The results of the regression estimates are presented in Figure 3, which shows the distribution of the estimated coefficients of the interaction term $Treat_i \times After_t$ from the placebo test along with their *p*-values. The horizontal line indicates a *p*-value of 0.1, and the vertical line indicates the genuine estimates from the baseline regression with the actual treatment and control groups, which were −0.287 for Ln(AQI) and −0.332 for Ln($PM_{2.5}$). Figure 3a shows that most of the simulated estimates for Ln(AQI) fell within the range of −0.2 to 0. with *p*-values greater than 0.1, indicating that our estimate was an outlier and not a chance result generated by random simulation. Figure 3b shows that most of the simulated estimates for Ln($PM_{2.5}$) also had *p*-values more significant than 0.1, except for a few cases that were close to zero, indicating that our estimate was significantly different from the simulated values, confirming that hosting the Beijing Winter Olympics improved the air quality in the Beijing–Tianjin–Hebei region. This finding was consistent with the baseline regression, indicating that our main results were robust.



(**a**) (**b**)

Figure 3. The results of the placebo test for Ln(AQI) and Ln($PM_{2.5}$). (**a**) Placebo test for Ln (AQI); (**b**) placebo test for Ln ($PM_{2.5}$). The figure was produced by Stata/MP 17.0 [57].

4.2.3. Variable Substitution

The robustness of the regression results of Equation (1) was evaluated using variable substitution, with PM_{10} and NO_2 representing air quality for the regression analysis, respectively. The regression results of the variable substitution shown in Table 4 revealed that holding the Winter Olympics reduced PM_{10} levels by about 26% and NO_2 levels by about 24% without the control variables, both being significant at the 1% level; with the control variables, the reductions were 27% and 20%, respectively. Whether the AQI, $PM_{2.5}$ or PM_{10} levels, or NO_2 levels were used to measure the air quality in the Beijing–Tianjin–Hebei region, the Beijing Winter Olympics significantly positively impacted the above air quality indicators.

Table 4. Variable substitution test.

Variables	(1) Ln (PM_{10})	(2) Ln (NO_2)	(3) Ln (PM_{10})	(4) Ln (NO_2)
$Treat_i \times After_t$	−0.306 *** (0.092)	−0.269 *** (0.089)	−0.310 *** (0.088)	−0.253 *** (0.072)
Control variables	No	No	Yes	Yes
Constant	4.557 *** (0.057)	3.469 *** (0.056)	3.730 *** (0.248)	2.764 *** (0.223)
Observations	252	252	252	252
R-squared	0.230	0.111	0.535	0.408

Note: standard errors are in parentheses. *** $p < 0.01$.

4.3. Heterogeneity Analysis

In this section, we aim to examine the heterogeneous impacts of the Beijing Winter Olympics on cities with different characteristics and to answer the following questions: Do more polluted cities experience a more significant improvement in air quality during the preparation for the Beijing Winter Olympics? Does the distance from the capital affect the effect of the Winter Olympics on air quality? Do differences in the degree of economic development affect air quality in different cities?

4.3.1. Effect of Pollution Status

To examine whether the impact of the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region exhibited variability under different pollution conditions, we conducted a triple difference test from the pollution status of each area. We set the dummy variable "*Pollution*" for the pollution status to 1 for the cities with an AQI that was more significant than 100 and 0 for the other cities (since an AQI greater than 100 means that air pollution is occurring). The model estimation equation is as follows:

$$Y_{it} = \alpha + \theta_1 Treat_i \times After_t \times Pollution_i + \beta_2 Treat_i \times After_t + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

In Equation (3), θ_1 represents this study's coefficient of vital interest. θ_1 indicates the degree of improvement in air quality in cities with more severe air pollution after a successful bid to host the Beijing Winter Olympics. $Treat_i$ is a dummy variable, where $Treat_i$ = 1 for the cities in the Beijing–Tianjin–Hebei region and $Treat_i$ = 0 for the control cities. $After_t$ is also a dummy variable indicating the period, where $After_t$ = 1 means after the successful bid for the Beijing Winter Olympics; otherwise, $After_t$= 0. The meanings of the other variables are the same as in Equation (1). The estimation results of the model are shown in Panel (A) in Table 5. The coefficient of the triple interaction term $Treat_i \times After_t \times Pollution_i$ was 0.203. It was significant at the 1% level, which means that the effect of the Beijing Winter Olympics on air quality improvement in polluted cities was more effective than that in non-polluted cities.

Table 5. Results of the heterogeneity analysis.

Variables	Panel A	Panel B	Panel C
$Treat_i \times After_t \times Pollution_i$	0.203 *** (0.036)		
$Treat_i \times After_t \times Distance_i$		0.728 *** (0.045)	
$Treat_i \times After_t \times PGDP_i$			0.001 (0.001)
$Treat_i \times After_t$	−0.369 *** (0.051)	−3.454 *** (0.263))	−0.001 (0.001)
Control variables	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
City effects	Yes	Yes	Yes
Constant	3.697 *** (0.145)	6.879 *** (0.428)	0.001 (0.001)
Observations	252	252	252
R-squared	0.544	0.879	1.000

Note: standard errors are in parentheses. *** $p < 0.01$.

4.3.2. Impact of Capital City Distance

To examine whether the impact of the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region exhibited variability in the distance from the capital city (Beijing), we constructed a triple difference test based on the difference in the distance from the capital city in each region. To measure the distance from the capital city, we built a dummy variable, "*Distance*", based on the geographical coordinates of each city. We obtained the latitude and longitude of each city from an online database (http://www.jsons.cn/lngcode (accessed on 2 May 2023)) and then calculated the great-circle distance between each city and Beijing using a latitude and longitude distance calculator (https://tools.fun/distance.html (accessed on 2 May 2023)). The model estimation equation is as follows:

$$Y_{it} = \alpha + \theta_2 Treat_i \times After_t \times Distance_i + \beta_2 Treat_i \times After_t + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

In Equation (4), θ_2 represents the coefficient of vital interest in this study, which indicates the extent to which the distance from the capital city improved the air quality during the preparation for the Beijing Winter Olympics. The meanings of the other variables are the same as in Equation (1). As shown in Panel (B) in Table 5, the triple interaction term $Treat_i \times After_t \times Distance_i$ coefficient was 0.728. It was significant at the 1% level, which implies that the Beijing Winter Olympics had a more powerful positive impact on cities further away from the capital.

4.3.3. Effect of the Degree of Economic Development

To examine whether the impact of the Beijing Winter Olympics on urban air quality showed variability for cities with greater economic development, we constructed a triple difference test from the regional differences in the degree of economic growth. Greenstone et al. (2021) conducted a spatial heterogeneity analysis of air quality in China from 2013–2018. They found that the higher the degree of economic development, the more significant the improved air quality in cities and the more pronounced [59]. To measure each city's economic development degree, we used the per capita gross regional product (PGDP) as an indicator. PGDP is calculated as the urban GDP divided by the urban population. We also constructed a dummy variable, "*PGDP*", to capture the effect of economic development on the outcome variable. The model estimation equation is as follows:

$$Y_{it} = \alpha + \theta_3 Treat_i \times After_t \times PGDP_i + \beta_2 Treat_i \times After_t + \gamma X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

In Equation (5), θ_3 represents this study's coefficient of vital interest. The meanings of the other variables are the same as in Equation (1). As shown by Panel (C) in Table 5,

$Treat_i \times After_t \times PGDP_i$ was insignificant at the 5% level, indicating no significant effect of urban economic development differences on improving urban air quality by the Beijing Winter Olympics. This suggests that government actions were more influential than market economies in preventing and controlling air pollution related to the Winter Olympics. The reason for the discrepancy between our findings and those of Greenstone et al. (2021) was that their study only demonstrated a statistical correlation between the degree of economic development and improvement in air quality [60].

5. Discussion

In this study, we investigated the impact of the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region and its contribution to sustainable development. Our work makes several significant contributions to the existing literature. First, we used DID method to analyse the impact of the Beijing Winter Olympics on air quality. This model allowed us to compare the changes in air quality between the treated and control groups, eliminating the effects of seasonal and annual variations in air quality. As a result, we could more accurately assess the impact of the Beijing Winter Olympics on air quality. Second, we provided a more comprehensive picture of the impact of the Beijing Winter Olympics on air quality by considering the air quality changes in the cities hosting the Winter Olympics (Beijing and Zhangjiakou) and the neighbouring cities. Air quality is not only influenced by local emissions but also by surrounding areas, and our study took this into account.

Our findings indicated that the Beijing Winter Olympics had a significantly positive effect on the air quality in the Beijing–Tianjin–Hebei region, which was consistent with previous studies on Olympic air quality in China and other areas (e.g., Ventura et al. (2019) [60] Liu et al. (2022) [25]). Furthermore, our trend analysis suggested that the impact of the Beijing Winter Olympics on air quality was sustainable. The Winter Olympics was committed to conducting a "carbon-neutral" event and applied sustainable practices throughout the bidding, planning, and hosting processes [36]. Additionally, all competition venues used 100% clean energy for their power supply, and ecological restoration works were designed, constructed, and accepted simultaneously [61].

We used economic indicators as the control variables, including GDP, fiscal revenue, and fiscal expenditure, but we found no significant effect of GDP and fiscal revenue on the DID estimation results. This indicates the neutral impact of economic indicators on air quality, i.e., economic indicators do not influence air quality and do not affect changes in economic indicators. This finding was consistent with the study by Li et al. [62]. This paper's research methods and results have important implications and insights for understanding the Beijing Winter Olympics' environmental impacts and developing effective air quality policies.

Our study has some important policy implications. First, this study's results can help policymakers to assess the extent of the impact of the Beijing Winter Olympics on air quality and the effectiveness of the environmental protection measures, thus providing a basis for the development of more scientific and practical environmental protection policies. Second, this study of the impact of the Beijing Winter Olympics can summarise the laws and characteristics of the impact of large-scale events on the environment, thus providing experience for the environmental impact assessment of similar events in the future. Finally, this study's results can also help policymakers to understand the current situation and shortcomings of air environment management in the Beijing–Tianjin–Hebei region and provide references for strengthening synergistic regional development and promoting environmental management.

However, there is still room for improvement in our study. First, to enhance the precision of our analysis, future research can employ more advanced models and methods, such as machine learning algorithms and deep learning models, that can overcome some of the drawbacks of traditional statistical models. Machine learning and deep learning can learn from data and make predictions without relying on strict assumptions or predetermined parameters. They can also handle complex and nonlinear relationships between variables and deal with large-scale and high-dimensional data [63]. Second, to improve the accuracy and reliability of data, future research can adopt more scientific data collection methods, such as remote sensing technology and drone monitoring, that can capture the spatial and temporal variations in air pollution. Third, future research can compare different governance strategies and measures that target various pollution sources and pollutants to evaluate the effectiveness of air-pollution-treatment strategies. Fourth, we did not include traffic volume, engine, and fuel type data in our control variables, which may have also affected the air quality in the region. Due to the difficulty of obtaining these data, we did not include them in our DID model. However, these factors may have introduced some bias in our estimation results, so future studies can try to collect these data and incorporate them into the DID model to assess the impact of the Beijing Winter Olympics on the air quality in the Beijing–Tianjin–Hebei region more accurately. Finally, to provide policy implications, future research can explore how policy implementation can be optimised to develop more scientific and reasonable air-pollution-management policies.

6. Conclusions

This study assessed the effects of the Beijing Winter Olympics on air quality using the DID method. The results imply that the Beijing Winter Olympics significantly improved the air quality in the region's cities. There was an average decrease of 25% in the AQI and 28% in $PM_{2.5}$ levels. This study conducted robustness tests and a heterogeneity analysis to ensure the validity of the significant findings. The survey results confirmed the main findings and showed that pollution and the distance from the capital positively impacted air quality and that a city's economic development level had no significant impact on improving air quality. However, such improvements should not lead to complacency. China must implement stricter environmental protection regulations and standards to enhance air quality sustainably.

Furthermore, developing and applying clean energy should be encouraged and supported to reduce the dependence on fossil fuels and improve air quality. This study's findings showed that the Beijing Winter Olympics positively impacted the air quality in the Beijing–Tianjin–Hebei region. Nonetheless, continued efforts are required to maintain and further improve the air quality in the area.

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