sustainability

Article

Population Mobility and Urban Air Quality: Causal Inference and Impact Measurement

Fu Huang [1,2], Qiang Wu [1,2,*] and Pei Wang [1,2]

1 Yangtze River Delta Economics and Social Development Research Center, Nanjing University, Nanjing 210093, China; dg20020029@smail.nju.edu.cn (F.H.)
2 School of Economics, Nanjing University, Nanjing 210093, China
* Correspondence: qiangwu@nju.edu.cn; Tel.: +86-139-1296-1567

Abstract: This paper treats the lockdown of Hubei Province during the outbreak of COVID-19 in early 2020 as a quasi-experiment, and uses the prefecture-level data of 328 cities in China to identify the causal effects of population mobility and urban air quality. This paper uses the DID model to eliminate the 'Spring Festival effect' with data from the same period of the lunar calendar in 2019 as the control group, and finds the reduction in population mobility has a clear causal impact on the improvement of urban air quality. The vast majority of air pollutants decreased, but ozone, which has a special generation mechanism, increased. This paper also constructs 29-day panel data of 328 prefecture-level cities from January to February in 2020 to quantitatively estimate the impact of population flow on urban air quality. After controlling for fixed effects, the results reveal that 1% increases in intra-city and inter-city population flows correspond to respective increases of 0.433% and 0.201% in the urban air quality index. Compared with inter-city flow, intra-city population flow increases air pollution more severely.

Keywords: population mobility; urban air quality; quasi-natural experiment

check for updates

Citation: Huang, F.; Wu, Q.; Wang, P. Population Mobility and Urban Air Quality: Causal Inference and Impact Measurement. *Sustainability* **2023**, *15*, 11591. https://doi.org/10.3390/su151511591

Academic Editor: Weixin Yang

Received: 29 May 2023
Revised: 20 July 2023
Accepted: 24 July 2023
Published: 27 July 2023

1. Introduction

As China's urbanization level continues to improve, economic activities are becoming more and more concentrated at the spatial scale of cities, and urban air pollution is becoming increasingly serious. Urban air quality is an important issue for people's livelihoods and is closely related to the health and well-being of urban residents, which is why the issue of urban air quality has received widespread attention from all sectors of society in recent years. The Chinese government attaches great importance to this issue, and green development has become an important part of its new development concept. The Fifth Plenary Session of the 19th Central Committee of the Communist Party of China proposed that the 14th Five-Year Plan period should achieve new progress in the construction of ecological civilization, a continuous reduction in the total emissions of major pollutants, and a continuous improvement in the ecological environment. Urban air quality has become one of the binding indicators for China's economic and social development in the 14th Five-Year Plan, and the ratio of good air quality days in cities at the prefecture level and above should be increased to 87.5% (according to the 14th Five-Year Plan and the Long-Range Objectives Through the Year 2035 for the National Economic and Social Development of the People's Republic of China). Therefore, it is important to study the main determinants of urban air quality, identify the causal impact of these factors on urban air quality, and quantify the magnitude of their impact in order to scientifically formulate policies to solve urban air pollution problems.

Theoretical research into the determinants of urban air quality in China has produced a wealth of results. The foremost determinants are urban traffic conditions and transport infrastructure. Traffic congestion increases vehicle emissions and contributes to air pollution [1], while increased investment in transport infrastructure will improve urban air quality by increasing road space [2]. For intra-city travel, the opening of rail lines is effective in combating urban air pollution [3], but car restriction policies do not significantly improve urban air quality [4]; for inter-city travel, the opening of high-speed rail significantly improves urban air quality, and the more extensive the high-speed rail network, the more significant the emission reduction effect brought by high-speed rail [5,6]. The second most important determinants of urban air quality are population concentration and urban expansion. Xu et al. [7] argued that population agglomeration has a "U"-shaped effect on environmental pollution emissions, Zhou and Zhang [8] found that new urbanization aggravates air pollution through population and production factors, and Wang and Shi [9] pointed out that low-carbon city construction can reduce haze pollution. Current research on the impact of urban expansion on urban air quality has different views, with some studies suggesting that urban expansion has a suppressive effect on environmental pollution [10] and others arguing that urban expansion exacerbates urban air pollution [11] and that urbanization is an important factor affecting urban air quality [12]. Some scholars have also studied the effects of factors such as official turnover [13,14], export trade [15], government behavior [16], and environmental regulation [17] on urban air quality. In addition, some scholars have conducted research on the urban heat island effect [18] and the impact of human activities on the ecological environment [19].

This paper seeks to examine the impact of population movements on urban air quality. Within the city limits, human activity is clearly the most significant factor influencing air quality, and the types of factors studied in the literature above are a reflection of human activity. Population movement, which is directly related to urban traffic conditions and transport infrastructure, is the underlying behavior in these human activities, and the movement of people within and between cities forms the micro-foundation of population clustering and urban expansion. In this sense, population movement may be a key factor affecting urban air quality at a deeper level.

However, when identifying the causal impact of population mobility on urban air quality, one faces endogeneity and estimation biases due to reverse causality. Numerous studies have shown that urban air pollution has a significant negative impact on the employment location of mobile populations [20], that population mobility prefers cities with good ecological construction [21], and that a good environment attracts environmental migrants and provides sustainable human capital for local economic development [22], especially for high-human capital groups [23]. After the outbreak of COVID-19 in early 2020, the Chinese government promptly took various preventive and control measures to effectively control the spread of the epidemic, one of the most significant measures being the lockdown of cities. City closures are exogenous in that they directly reduce the scale of population movement, both within and between cities, which cuts off the reverse causal effect of urban air quality on population movement and provides a key exogenous window of impact event for accurately identifying the causal effect of population movement on urban air quality. It is due to this exogeneity that some foreign scholars have begun to study the impact of various types of closure measures taken for epidemic prevention and control on local air quality [24,25] and on major air pollutants [26]; some Chinese scholars have also focused on the economic effects of epidemic prevention and control measures [27,28]. However, no results have yet emphasized the identification of causal relationships between population movements and urban air quality, or the role of exogenous measures such as city closures; additionally, quantitative measures of such causal effects are also lacking.

The possible marginal contributions of this paper lie in three areas. First, the topic is novel, as although there is a large literature on the factors influencing urban air quality, there are relatively few studies that have analyzed it from the perspective of population mobility, and few studies that have quantified this effect. Second, a standard DID model is used for causal identification, and data from the same period of the 2019 lunar calendar is used as a control group to eliminate the "Chinese New Year effect". Third, data crawling is combined with matching use. This paper uses Python crawling techniques to obtain data on population movement, air quality and weather conditions, and matches these data according to city names.

2. Data and Methods

2.1. Theoretical Framework

The difficulty in identifying the causal impact of population movements on urban air quality is twofold. On the one hand, it is difficult to have a window period in which population movement changes dramatically, and it is common for population movement data to have a low degree of variability over sample periods; on the other hand, urban air quality changes can, in turn, affect population movement behavior, increasing the potential for endogeneity bias due to reverse causation. In early 2020, to prevent the spread of COVID-19, cities in Hubei Province took measures to close the city under the unified deployment and leadership of the Chinese government. Wuhan COVID-19 Pandemic Prevention and Control Headquarters first issued Circular No. 1 on 23 January, suspending public transport in the city and restricting passage out of Wuhan; subsequently, cities in Hubei issued city lockdown circulars one after another, until Xiangyang was officially closed on 28 January and all cities in the whole of Hubei went into lockdown. This paper uses the city closure policy adopted by Hubei cities as an exogenous shock event which both directly reduces population movement and does not have the reverse causal endogeneity of urban air quality affecting population movement, providing a valuable window period for identifying the impact of population movement on urban air quality. Therefore, this paper employs the difference-in-differences (DID) method for modeling. The difference-in-differences (DID) method is a commonly used analytical approach for policy research, and its underlying principle is similar to that of a natural experiment. It treats the implementation of a particular policy as a natural experiment, comparing and analyzing the treatment group, which is subject to the policy, with the control group, which is not affected by the policy, in order to examine the net impact of the policy on the analyzed variables.

At the same time, as the outbreak of COVID-19 in early 2020 coincided with the Chinese Lunar New Year holiday, the causal identification in this paper must take into account the fact that, during the Lunar New Year holiday, most of China celebrates the Chinese New Year, shutting down production and naturally reducing air pollution levels [29]. Therefore, in this paper, we use data from 2020 and 2019, rather than just 2020, to avoid the "Chinese New Year effect" [30]. Specifically, this paper uses data from the 23rd day of the 23rd month of the lunar calendar to the 28th day of the first month of the lunar calendar in Hubei in 2020 and data from cities outside Hubei in the same period of the 2019 lunar calendar, with the 2020 Hubei cities as the treatment group and the rest of the Chinese cities in the same period of the 2019 lunar calendar as the control group. In the baseline regression part of the causal identification, considering that, although the cities in Hubei declared city closures in a slight sequence, most Hubei cities declared city lockdowns on 24 January, with six cities declaring city lockdowns, and the vast majority of Hubei cities declaring city closures two days before and after 24 January, this paper chooses to take 24 January, i.e., Lunar New Year's Eve, as the time point of the policy shock. This is also, in fact, the most critical date for all cities in Hubei Province to actually adopt the city lockdown policy.

Analyzing the actual situation, the five Hubei cities that announced the implementation of city lockdowns on 25 and 28 January were actually close to the status of city lockdown after other cities had announced it. Therefore, the choice of Lunar New Year's Eve as the policy impact point in the benchmark regression is in line with the real situation of city lockdown in Hubei. However, in terms of the timing of the announcement, Wuhan and Ezhou were closed on 23 January; Huangshi, Jingmen, Jingzhou, Huanggang, Xianning, and Enshi were closed on 24 January; Shiyan, Yichang, Xiaogan, and Suizhou were closed on 25 January; and Xiangyang was closed on 28 January. The timing of the announcement of the city closure in each city in Hubei is sequential, and using 24 January as the timing of the policy shock uniformly may weaken the credibility of the causal identification. Therefore, this paper also constructs a multi-period DID model to verify the robustness of the benchmark regression by using the city lockdown dates announced by each city in Hubei as the respective policy shock points.

In terms of specifically quantifying the magnitude of the impact of population movement on urban air quality, this paper divides population movement at the city level into two components: intra-city population flow, which refers to population moving within cities, and inter-city population flow, which refers to population moving between cities. The magnitude of the impact of these two types of population movement on urban air quality may differ and needs to be measured separately. Based on this, this paper introduces the intra-city population flow variable, $lnincity$, and the inter-city population flow variable, $lnoutcity$. Baidu Migration provides data on the scale of these two types of population flow, so this paper takes the intra-city travel intensity recorded by Baidu Migration, absolutizes the index using the approach of Fang et al. [31], and then takes its logarithmic value as the intra-city population flow variable, $lnincity$; then, the city in-migration scale index and city out-migration scale index of Baidu Migration are absolutized, and their logarithmic values are taken after summing to obtain a measure of the inter-city population mobility variable, $lnoutcity$. In this section, intra-city population flow and inter-city population flow are used as the main explanatory variables in turn, and static panel fixed effects models are used to measure the magnitude of the specific effects of these two on urban air quality, respectively.

2.2. Model Selection

The baseline regression component of the causal identification in this paper sets up a DID model, as shown in Equation (1), to identify whether a reduction in population movement can have a causal impact on urban air quality improvement.

$$Urpollu_{it} = \alpha + \beta treat_i * post_t + \gamma X_{it} + u_i + \eta_t + \varepsilon_{it} \quad (1)$$

Here, i and t denote city and time, respectively. The explanatory variable for urban air quality, $Urpollu_{it}$, is measured using a set of indicators, specifically the urban air quality index, AQI, and levels of six major air pollutants, $PM2.5$, $PM10$, SO_2, CO, NO_2, and O_3. The main explanatory variable is $treat_i * post_t$, where $treat_i$ is a dummy variable for the treatment group within Hubei Province and $post_t$ is a dummy variable for the implementation of the city closure policy in Hubei, with a value of 1 for New Year's Eve and beyond and 0 for before New Year's Eve. X_{it} is a set of control variables specifically including the local maximum and minimum temperatures, wind levels, and their squared terms for that day. This paper further controls for city fixed effects, u_i, and time fixed effects, η_t, while ε_{it} is a random error term.

In this paper, a multi-period DID model, as shown in Equation (2), is set up in the causal identification robustness test section.

$$Urpollu_{it} = \alpha + \beta D_{it} + \gamma X_{it} + u_i + \eta_t + \varepsilon_{it} \quad (2)$$

The main explanatory variable, D_{it}, is the cross multiplier between cities in Hubei Province and the implementation of city closure policies; if city i in Hubei Province announces the implementation of the city closure policy at time t, then the value of D_{it} for that city at time t and later will be 1, otherwise it will be 0. The explanatory variable, $Urpollu_{it}$, remains logarithmic, and the control variables and fixed effects are set as shown in Equation (1).

Based on the causal identification, Equation (3) is set up in this paper to estimate the magnitude of the effect of population movement on urban air quality.

$$Urpollu_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \varepsilon_{it} \tag{3}$$

Here, i and t denote area and time, respectively. The explanatory variable, $Urpollu_{it}$, is also a set of indicators measuring urban air quality from various aspects, specifically the urban air quality index, $lnAQI$, and the main air pollutants, $lnPM2.5$, $lnPM10$, $lnSO_2$, $lnCO$, $lnNO_2$, and lnO_3, all of which are taken as logarithmic values. The main explanatory variable, X_{it}, is the intra-city population flow variable, $lnincity$, and the inter-city population flow variable, $lnoutcity$, in that order. Z_{it} is a set of control variables specifically including the local maximum and minimum temperatures, as well as the wind level and its squared term on a given day, while ε_{it} is a random error term. This paper uses a static panel fixed effects model to estimate Equation (3), with standard error clustering at the city level.

2.3. Data Sources

This paper constructs panel data covering 36 days for 328 prefecture-level cities in China, matching three aspects: air quality, weather, and population movement. The air quality-related data are crawled from the historical data of the China Air Quality Online Monitoring and Analysis Platform (www.aqistudy.cn), including AQI, $PM2.5$, $PM10$, SO_2, CO, NO_2, and O_3 levels. Higher values of these data indicate poorer air quality. Weather-related data were crawled from weather.com (www.tianqi.com) historical data, specifically including the highest temperature of the day, the lowest temperature of the day, and wind; population movement data were crawled from Baidu Migration (qianxi.baidu.com) historical data, specifically including the urban migration size index and intra-city travel intensity. The treatment group includes data for cities in Hubei for 36 consecutive days from 17 January to 21 February 2020, and the control group includes data for cities outside Hubei for 36 consecutive days from 28 January to 4 March 2019. The population movement data in this paper is sourced from Baidu Migration, which may lead to a potential underestimation of population movement, as Baidu Migration is unable to track the movements of every individual. However, this is the closest approximation of population movement data available for this study.

As the population migration data in Baidu Migration are all relative indicators, this paper follows the approach of Fang et al. [31] and absolutizes them. Fang et al. [31] first collected the actual number of people entering and leaving Shanghai from 6–22 February 2020 from the National Earth System Science Data Centre, then compared the in-migration scale and out-migration scale indices of Shanghai in Baidu Migration in the same period, and estimated that the actual number of people corresponding to each unit of the city in-migration and out-migration scale indices was 90,848 and the actual number of people corresponding to each unit of intra-city travel intensity was 2,182,264 persons. This paper uses their estimated conversion values and converts them to obtain the actual number of people moving in and out of each city per day. Table 1 shows the descriptive statistics of the raw data for the variable measures. In Table 1, "Unit" represents the unit of measurement for the variable. "AQI" is a dimensionless index that does not have a unit. "Wind" is categorized by wind strength levels and does not have a unit. "N" represents the sample size.

Table 1. Definition of variables and descriptive statistics.

Variable	Unit	N (Sample Size)	Mean	Std. Dev.	Min	Max
AQI	/	11,808	83.693	56.235	0	500
PM2.5	$\mu g/m^3$	11,808	56.134	46.426	0	536
PM10	$\mu g/m^3$	11,808	84.740	66.863	0	1141
SO_2	$\mu g/m^3$	11,808	13.497	12.797	0	362
CO	mg/m^3	11,808	0.982	0.436	0.1	4.4
NO_2	$\mu g/m^3$	11,808	26.738	16.542	0	110
O_3	$\mu g/m^3$	11,808	71.397	24.838	4	294
Highest temperature	°C	11,808	8.944	8.851	−25	33
Lowest temperature	°C	11,808	−0.091	9.756	−38	25
Wind	/	11,808	2.156	0.769	0	6
Num of people moving into city	10 K people	11,808	12.216	17.039	0.008	237.639
Num of people moving out of city	10 K people	11,808	12.167	15.314	0.017	199.394
Num of people traveling within the city	10 K people	11,808	964.674	226.978	125.240	1922.706

3. Results

3.1. Baseline Regression Test

Table 2 shows the estimation results of Equation (1), with the explanatory variables in Columns (1)–(7) being AQI, $PM2.5$, $PM10$, SO_2, CO, NO_2, and O_3, respectively. Meanwhile, Figure 1 displays the visualized results of the magnitude of the coefficient estimates and their confidence intervals for the seven explanatory variables.

Table 2. Baseline regression for causal identification of reduced population movement to improve urban air quality.

	(1) *AQI*	(2) *PM2.5*	(3) *PM10*	(4) SO_2	(5) *CO*	(6) NO_2	(7) O_3
$treat_i * post_t$	−40.129 ***	−36.190 ***	−37.691 ***	−0.282	−0.174 ***	−16.635 ***	6.193 ***
	(5.445)	(4.228)	(4.139)	(0.524)	(0.038)	(0.950)	(1.878)
Lowest temperature	0.530 **	0.657 ***	0.624 **	−0.128 ***	0.000	0.030	−0.841 ***
	(0.261)	(0.204)	(0.294)	(0.047)	(0.002)	(0.062)	(0.155)
Highest temperature	2.917 ***	2.323 ***	3.603 ***	0.306 ***	0.023 ***	0.748 ***	1.416 ***
	(0.337)	(0.261)	(0.398)	(0.104)	(0.003)	(0.072)	(0.136)
Wind	−13.824 ***	−8.991 ***	−16.962 ***	0.092	−0.115 ***	−5.717 ***	−2.050
	(2.737)	(1.997)	(3.295)	(0.661)	(0.025)	(0.732)	(1.251)
Lowest temperature^2	0.026 ***	0.021 **	0.038 ***	0.001	0.000 *	0.011 ***	−0.022 ***
	(0.010)	(0.008)	(0.012)	(0.002)	(0.000)	(0.003)	(0.005)
Highest temperature^2	−0.016	−0.007	−0.034 ***	0.006	−0.000 ***	0.006 **	0.057 ***
	(0.011)	(0.009)	(0.012)	(0.005)	(0.000)	(0.003)	(0.005)
Wind^2	1.350 **	0.228	2.588 ***	−0.335 ***	0.003	0.119	0.380
	(0.526)	(0.378)	(0.653)	(0.127)	(0.004)	(0.144)	(0.232)
Constant	103.052 ***	71.869 ***	93.102 ***	7.790 ***	0.972 ***	50.886 ***	51.997 ***
	(4.125)	(3.176)	(4.945)	(0.815)	(0.034)	(1.014)	(2.185)
Sample size	11,808	11,808	11,808	11,808	11,808	11,808	11,808
R-squared	0.566	0.594	0.602	0.618	0.575	0.738	0.508
Time FE	YES	YES	YES	YES	YES	YES	YES
Urban FE	YES	YES	YES	YES	YES	YES	YES

Note: Figures in brackets are clustering robustness criteria errors; *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

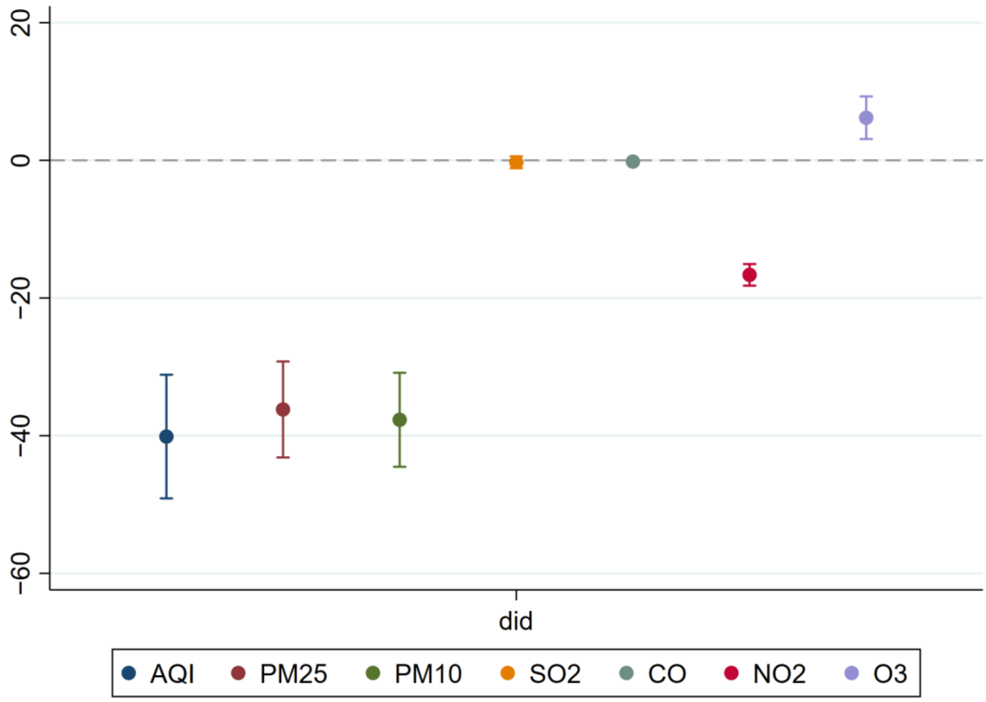

Figure 1. The coefficient estimates and confidence intervals for the seven explanatory variables. Note: "did" represents the interaction term "treat ∗ post".

In Table 2, when the explanatory variable is the AQI, the $treat_i * post_t$ coefficient is significantly negative, indicating that the reduction in population movement has led to an overall improvement in urban air quality. The $treat_i * post_t$ coefficients are also significantly negative when the explanatory variable is one of the major air pollutant indicators ($PM2.5$, $PM10$, CO, and NO_2), indicating that the reduction in population movement has led to a significant reduction in the concentration of these four major air pollutants in the air. When the explanatory variable is SO_2, the $treat_i * post_t$ coefficient is negative but not significant. Although the reduction in population movement leads to a reduction in the concentration of SO_2 in the air, this causal effect is weak and does not pass the statistical significance test. In addition, the $treat_i * post_t$ coefficient is significantly positive when the explanatory variable is O_3, indicating that the reduction in population movement leads to a significant increase in the concentration of O_3 in the air instead.

3.2. Parallel Trend Hypothesis Test

For the results of the DID method test to be unbiased and reliable, its experimental and treatment groups must satisfy the parallel trend assumption. In this paper, we adopt the event study method, referring to Luo et al. [32], use New Year's Eve as the event impact point, and select four days before and after for the parallel trend test. If the parallel trend hypothesis holds, then there should be no significant difference in the trend of urban AQI changes between the treatment and control groups before New Year's Eve. Figure 2 shows the results when the explanatory variable is the urban AQI. The x-axis represents the time before and after policy implementation, while the y-axis represents the impact of the policy effects. The results indicate that there is no significant difference in the overall urban air quality change trend between the treatment and control groups before the policy shock, i.e., the parallel trend hypothesis holds; after the policy shock occurs, there is a significant negative effect on the urban AQI. To save space, we have provided the parallel trend hypothesis test results for the six major air pollutants as explanatory variables in Appendix A. Please refer to Figures A1–A6 for details. Five of major air pollutants passed the parallel trend hypothesis test, demonstrating that, overall, the baseline regression results in Table 2 are plausible. Only SO_2 does not pass this test, which does not fundamentally change the conclusions, as the interaction term $treat_i * post_t$ is also not significant when the explanatory variable in the baseline regression is SO_2. This is another way of demonstrating the heterogeneous causal impact of reduced population movements on different air pollutants.

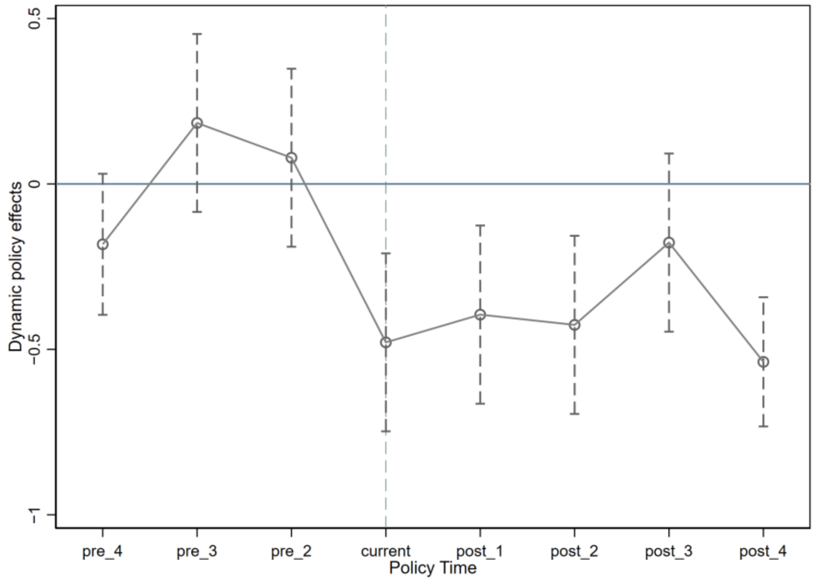

Figure 2. Results of parallel trend hypothesis testing where the explanatory variable is AQI. Note: Data for the pre_1 period is not available in the graph, as the first period before the policy shock is used as the base group.

3.3. Placebo Test

There may be other unobservable events prior to the occurrence of the city lockdown policy in Hubei cities in early 2020 that affect the veracity of the estimation results in this paper. To rule out the potential influence of such unobservable times on the estimation results, this paper uses a dummy policy shock point in time as a placebo method to identify whether such potential influence is real. A placebo test was conducted by using January 15, the date when the Chinese National Center for Disease Control and Prevention (CDC) initiated the Level 1 response, January 11, the date when the CDC provided PCR test strips to Wuhan, and January 8, the middle date of the two sessions in Wuhan, as the dummy shock dates in the original sample interval. To save space, we present the empirical results in Appendix B. The results of the placebo test for the explanatory variable AQI are shown in Table A1, where the $treat_i * post_t$ coefficients for Columns (1)–(3) were 1.038, 3.626, and −2.036, respectively, which did not pass the significance test, indicating that using these three time points as the policy shock dates did not have a significant impact on the overall air quality of the city. This suggests that using these three time points as policy shock dates did not have a significant effect on the overall urban air quality. The exogenous policy shocks in this paper are valid and the findings are robust, given that the causal effect of reduced population movement on urban air quality improvement due to the city lockdown policy in Hubei is real.

3.4. Robustness Tests

To further test whether the causal effect of reduced population mobility on urban air quality improvement is robust and reliable, this paper conducts robustness tests in two ways. Firstly, this paper replaces the explanatory variables. In this paper, the DID model of Equation (1) is estimated again by taking the logarithmic values of each measure of urban air quality in the baseline regression, and the results obtained are shown in Appendix C. Secondly, this paper uses a multi-period DID model. In this paper, the multi-period DID model of Equation (2) is estimated, and the results are shown in Appendix D.

The $treat_i * post_t$ coefficients of interest in this paper in Appendix C Table A2 are significantly negative when the explanatory variables are $lnAQI$, $lnPM2.5$, $lnPM10$, $lnSO_2$, $lnCO$, and $lnNO_2$, indicating that under the influence of reduced population movement, the urban air quality index, AQI, is significantly lower and the concentrations of the major air pollutants $PM2.5$, $PM10$, SO_2, CO, and NO_2 in the air are also significantly lower. Compared to the baseline regression, the interaction term ($treat_i * post_t$) coefficient, although becoming significant, is only significant at the 10% level when the explanatory variable is $lnSO_2$. When the explanatory variable is lnO_3, the interaction term ($treat_i * post_t$) is significantly positive, implying that the concentration of the main air pollutant (O_3) in the air increases significantly under the influence of reduced population movement, which is consistent with the baseline regression and the results are robust.

From the results in Appendix D Table A3, the results obtained from the D_{it} coefficients of interest in this paper remain consistent with the baseline regression under multi-period double difference estimation, again confirming the robustness of the causal identification results in this paper. Reduced population mobility does have a significant causal impact on urban air quality improvement.

3.5. Measuring the Impact of Intra-City Population Flow on Urban Air Quality

This paper empirically tests Model (3) with $lnAQI$, a measure of urban air quality, and $lnPM2.5$, $lnPM10$, $lnSO_2$, $lnCO$, $lnNO_2$, and lnO_3, the main explanatory variables, as the explanatory variables, respectively, and $lnincity$, a measure of intra-city population flow, as shown in Table 3.

Table 3. Results of measuring the impact of intra-city population flow on urban air quality.

	(1) $lnAQI$	(2) $lnPM2.5$	(3) $lnPM10$	(4) $lnSO_2$	(5) $lnCO$	(6) $lnNO_2$	(7) lnO_3
$lnincity$	0.433 ***	0.593 ***	0.516 ***	0.285 ***	0.273 ***	0.474 ***	0.050 ***
	(0.034)	(0.041)	(0.039)	(0.023)	(0.023)	(0.019)	(0.014)
Lowest temperature	0.001	0.021 ***	0.012 ***	−0.009 ***	0.013 ***	0.014 ***	−0.032 ***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Highest temperature	0.010 ***	0.010 **	0.015 ***	0.017 ***	0.010 ***	0.025 ***	0.024 ***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Wind	−0.118 ***	−0.171 ***	−0.164 ***	−0.147 ***	−0.110 ***	−0.211 ***	0.014
	(0.028)	(0.041)	(0.040)	(0.027)	(0.024)	(0.024)	(0.014)
Lowest temperature^2	−0.000 ***	0.000	0.000	−0.000 ***	0.000	0.000 **	−0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highest temperature^2	−0.000	−0.000	0.000	0.000	−0.001 ***	−0.000 ***	0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wind^2	0.002	−0.020 **	0.010	0.001	−0.008	−0.005	−0.004
	(0.005)	(0.009)	(0.008)	(0.006)	(0.005)	(0.005)	(0.002)
Constant	−2.403 ***	−5.251 ***	−3.951 ***	−2.062 ***	−4.196 ***	−4.395 ***	3.286 ***
	(0.523)	(0.639)	(0.598)	(0.347)	(0.360)	(0.290)	(0.210)
Sample size	9508	9508	9507	9508	9508	9508	9508
R-squared	0.125	0.212	0.127	0.187	0.194	0.428	0.265
FE	YES	YES	YES	YES	YES	YES	YES

Note: Figures in brackets are clustering robustness criteria errors; **, and *** denote significance levels of 5%, and 1%, respectively.

The results in Table 3 show that intra-city population flow does increase urban air pollution, both in terms of the urban air quality index indicator, $lnAQI$, and the main air pollutant indicators, $lnPM2.5$, $lnPM10$, $lnSO_2$, $lnCO$, $lnNO_2$, and lnO_3; all indicators increase with an increase in the intra-city population flow, and all results pass the 1% significance test.

3.6. Measuring the Impact of Inter-City Population Flow on Urban Air Quality

This paper empirically tests model (3) with $lnAQI$, a measure of urban air quality, and $lnPM2.5$, $lnPM10$, $lnSO_2$, $lnCO$, $lnNO_2$ and lnO_3, the main explanatory variables, as the explanatory variables, respectively, and $lnoutcity$, a measure of inter-city population flow, as shown in Table 4.

Table 4. Measured impact of inter-city population flow on urban air quality.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnAQI	*lnPM2.5*	*lnPM10*	$lnSO_2$	*lnCO*	$lnNO_2$	lnO_3
$lnoutcity$	0.201 ***	0.324 ***	0.235 ***	0.127 ***	0.158 ***	0.166 ***	0.043 ***
	(0.014)	(0.017)	(0.016)	(0.010)	(0.010)	(0.009)	(0.007)
Lowest temperature	0.005 **	0.028 ***	0.017 ***	−0.007 ***	0.016 ***	0.017 ***	−0.031 ***
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.001)
Highest temperature	0.011 ***	0.011 ***	0.015 ***	0.017 ***	0.010 ***	0.025 ***	0.025 ***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Wind	−0.110 ***	−0.160 ***	−0.155 ***	−0.142 ***	−0.104 ***	−0.204 ***	0.016
	(0.028)	(0.040)	(0.039)	(0.026)	(0.023)	(0.024)	(0.014)
Lowest temperature^2	−0.000 ***	0.000	0.000	−0.000 ***	0.000 *	0.000 ***	−0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highest temperature^2	0.000	0.000	0.000 **	0.000	−0.001 ***	−0.000	0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wind^2	0.003	−0.018 **	0.010	0.001	−0.007	−0.005	−0.003
	(0.005)	(0.008)	(0.007)	(0.005)	(0.005)	(0.005)	(0.002)
Constant	2.245 ***	0.619 ***	1.635 ***	1.049 ***	−1.593 ***	1.252 ***	3.617 ***
	(0.138)	(0.176)	(0.159)	(0.101)	(0.096)	(0.093)	(0.069)
Sample size	9508	9508	9507	9508	9508	9508	9508
R-squared	0.131	0.239	0.130	0.187	0.220	0.396	0.271
FE	YES	YES	YES	YES	YES	YES	YES

Note: Figures in brackets are clustering robustness criteria errors, *, ** and *** denote significance levels of 10%, 5% and 1%, respectively.

The results in Table 4 show that inter-city population flow increases urban air pollution. The urban air quality index indicator, $lnAQI$, and the main air pollutant indicators, $lnPM2.5$, $lnPM10$, $lnSO_2$, $lnCO$, $lnNO_2$, and lnO_3, all increase with inter-city population flow and are significant at the 1% level.

4. Discussion

4.1. Reduced Population Movements Significantly Improve Urban Air Quality

The results in the causal identification section of this paper confirm that a reduction in population movement can significantly improve urban air quality. After excluding the Chinese New Year effect, the strict city lockdown policies in Hubei cities exogenously restrict population movement, which fundamentally reduces all types of socio-economic activities and, in turn, reduces the emission levels of most air pollutants, resulting in significant improvements in urban air quality in the treatment group. However, it is also important to highlight that there is variability in the causal impact of exogenous reductions in population movement on various air pollutants, with significant reductions in $PM2.5$, $PM10$, CO, and NO_2 concentrations in the air, a statistically insignificant reduction in SO_2 concentrations, and a statistically significant increase in concentrations of O_3, which has a complex generation mechanism. The lack of significant reduction in SO_2 may be attributed to the fact that the lockdown measures primarily targeted vehicle exhaust emissions, while the emissions of sulfur dioxide could be more closely linked to heavy industries such as steel plants and coal-fired power stations that continued operating during the lockdown period.

Ozone concentrations increased significantly due to its specific generation mechanism. Environmental science research explains that this is partly due to a reduction in NO_x concentrations from human activities due to city lockdown policies, which slows down the rate of ozone decomposition, while increased human activity in the home leads to an increase in VOC_s concentrations; together, these factors accelerate ozone accumulation [33]. On the other hand, reduced haze due to reduced PM2.5 leads to easier penetration of sunlight into the air, providing more energy for surface ozone production [34]. Lv et al. [35], when studying why the greatly reduced traffic volume during the COVID-19 lockdown in Beijing did not effectively reduce haze pollution, found that the reduction in traffic volume resulted in a large-scale reduction in NOx emissions, but due to heating and other human activities, volatile organic compounds were reduced on a relatively small scale, resulting in an unbalanced reduction between them. This led to a significant increase in atmospheric oxidation capacity in urban areas, resulting in increased ozone pollution. Pei et al. [26] made use of observation data from remote sensing and field measurements and concluded that stable HCHO concentrations in urban areas provided sufficient fuel for the formation of O_3 in the troposphere. HCHO is an important proxy for volatile organic compounds. In addition, during the lockdown, NO in the atmosphere decreased significantly and could not provide stable decomposition for O_3, resulting in increased ozone. The above findings remind us that for China to achieve the goal of new progress in ecological civilization and sustainable improvement of the ecological environment, urban air pollutants with different generation mechanisms should be classified and specifically analyzed, and pollution reduction and emission reduction for various pollutants should be achieved precisely and gradually through scientific and integrated planning.

4.2. Both Intra-City and Inter-City Population Flow Contribute Significantly to Urban Air Pollution

According to the empirical results, for every 1% increase in intra-city population flow, the urban air quality index rises by 0.433% and the concentrations of the main air pollutants increase by 0.593% (PM2.5), 0.516% (PM10), 0.285% (SO_2), 0.273% (CO), 0.474% (NO_2), and 0.050% (O_3). Of these six major urban air pollutants, PM2.5 was the most influenced by intra-city population flow, followed by PM10 and NO_2, which may be related to the fact that intra-city population flow in China is dominated by motor vehicles, as fuel motor vehicle exhaust is the main source of low-level emissions in Chinese cities; PM2.5 and NO_x are the main pollutants in the exhaust of fuel-fired motor vehicles, and PM10 is also associated with motor vehicles.

According to the empirical results, for every 1% increase in inter-city population flow, the urban air quality index increases by 0.201%, and the concentrations of the main air pollutants increase by 0.324% (PM2.5), 0.235% (PM10), 0.127% (SO_2), 0.158% (CO), 0.166% (NO_2), and 0.043% (O_3). Of the six major urban air pollutants, PM2.5 was most affected by inter-city population flow, followed by PM10, and then NO_2 and CO, both of which were equally affected. With the exception of the majority of passenger trains, which are electrically powered and have only a marginal impact on air pollution, aircraft engine emissions and fuel motor vehicle exhaust, both of which contain PM, NOx, and CO, are likely to be the main contributors to this.

The estimated coefficient value of $lnoutcity$ for inter-city population flow is overall smaller than that of $lnincity$ for intra-city population flow, indicating that the magnitude of the negative impact of intra-city population flow on urban air quality is significantly greater than that of inter-city population flow in terms of urban air quality index indicators and major air pollutant indicators. This finding is enlightening, and implies that urban construction should be well researched and reasonably planned to shorten the commuting distance between work and residential areas, increase public transport facilities, and reduce the need for self-driving trips; at the same time, it should strengthen the construction of living facilities in residential areas, promote the integration of industries and cities, and reduce the need for long-distance travel within the city. This will improve urban air quality through a combination of measures to reduce the movement of people within the city.

4.3. Proposals for Achieving New Progress in Ecological Civilisation

In order to achieve the goals of new progress in ecological civilization, continuous reduction in total emissions of major pollutants, and continuous improvement of the ecological environment, this paper puts forward the following three policy recommendations. Firstly, further advocate and encourage green travel for the whole society, which is of utmost importance to the improvement of urban air quality. Electric vehicles should continue to be vigorously promoted as an alternative to fuel vehicles, vehicle emission standards should be upgraded, and the public should be encouraged to adopt public transport and shared travel and reduce private passenger travel. Secondly, the precise treatment of air pollutants with complex generation mechanisms, such as ozone, should be strengthened. This paper finds that after a significant reduction in population movement exogenesis, the concentration of a small number of major air pollutants such as ozone increased instead. This suggests that restricting the movement of people, or restricting economic activities such as industrial production, or adopting a "one-size-fits-all" approach to shutting down these air pollutants with complex generation mechanisms is not sufficient to reduce their harmful effects on urban air quality. The treatment and improvement of urban air quality requires further scientific research on the generation mechanisms of various air pollutants at the source, and precise and holistic measures in order to gradually promote pollution reduction and emission reduction. Thirdly, rational planning of urban layout is needed. The empirical results of this paper show that the pollution caused by intra-city population movement is significantly higher than that caused by inter-city population movement. Urban roads should be built to shorten the commuting distance between work and residential areas and to strengthen the construction of rail transport and public transport services; additionally, residential areas should strengthen the construction of living facilities to improve the convenience of residents' lives, so that most of their living and consumption needs can be solved in the vicinity of their homes, reducing the need to travel long distances within the city. For large cities in particular, the construction of new urban areas must be preceded by planning and scientific layout to create new urban areas with "city-industry integration" and planners should strive to realize the "integration of three places" of work, consumption, and residence for residents in the district, so as to avoid becoming a "bedroom community" in the central city, thus decreasing intra-city population flow.

5. Conclusions

The main objective of this paper is to empirically examine the causal impact of population movement on urban air quality and measure the specific magnitude of the effects of intra-city and inter-city population flow on urban air quality. This paper uses the city lockdown policy adopted by Hubei cities in early 2020 in response to the outbreak of the COVID-19 as a quasi-natural experiment with 328 prefecture-level cities in China to firstly identify the causal relationship between population movement and urban air quality, and secondly to measure the specific magnitude of the impact of the two types of population movement on urban air quality based on the distinction between intra-city and inter-city population flow. In the causal identification section, this paper uses data from the 23rd day of the lunar month to the 28th day of the first lunar month in Hubei in 2020 and the rest of Chinese cities in the same period in 2019 to construct a 36-day panel of air quality data for 328 cities, using the same period in the 2019 lunar calendar as a control group to eliminate the "Spring Festival effect". A DID method was used to find a causal effect of reduced population movement on urban air quality improvement. In the impact measurement section, the quantitative impacts of intra and inter-city population flow on urban air quality indices and major air pollutants were estimated using data from 328 prefecture-level cities in China for 29 consecutive days in January and February 2020. The results demonstrate that both intra-city and inter-city population flow have a significant negative impact on urban air quality. However, the specific impact coefficients differ, with an overall finding that an increase in intra-city population flow leads to a more severe level of air pollution.

This paper focuses on the causal identification and impact measurement of population movement on urban air quality. Future research directions related to this paper may involve clarifying the mechanisms through which population movement affects urban air quality. This would require obtaining more relevant data to support the research.

Author Contributions: Conceptualization, F.H. and Q.W.; methodology, F.H.; software, F.H.; validation, F.H., Q.W. and P.W.; formal analysis, P.W.; data curation, F.H. and P.W.; writing—original draft preparation, F.H.; writing—review and editing, Q.W.; supervision, Q.W.; project administration, Q.W.; funding acquisition, Q.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Major project of key research bases on Humanities and Social Sciences of the Ministry of Education, grant number 22JJD790037.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request.

Acknowledgments: Thanks to Wang Tianru for her advice and help in expressing this article in English.

Conflicts of Interest: The authors declare that they have no conflict of interest.

Appendix A

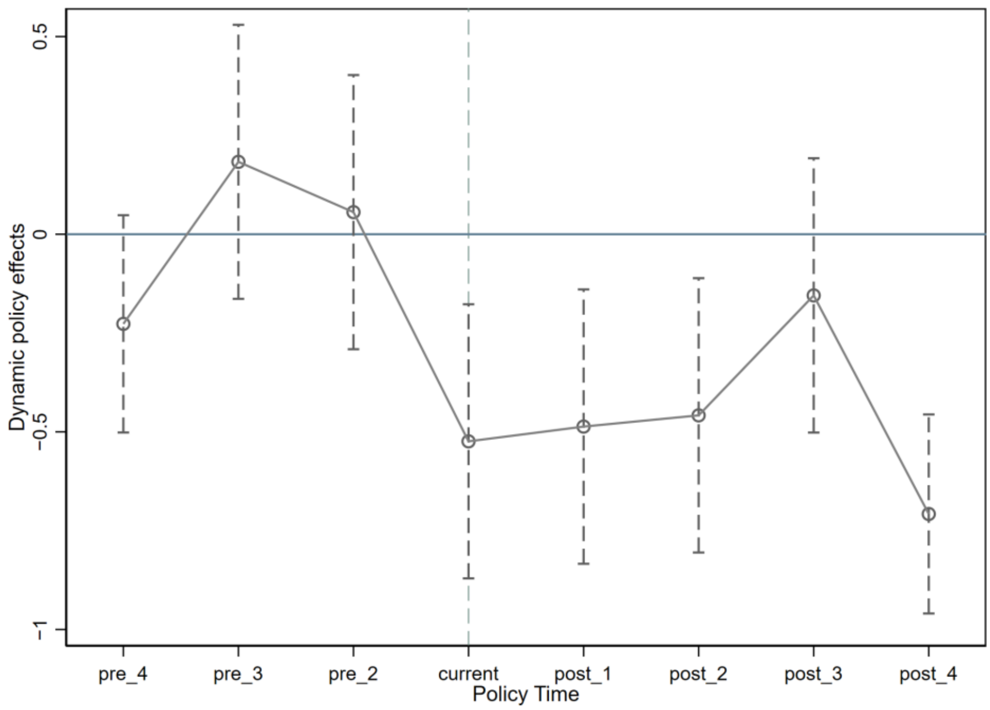

Figure A1. Results of parallel trend hypothesis testing where the explanatory variable is PM2.5. Note: Data for the pre_1 period is not available in the graph as the first period before the policy shock is used as the base group.

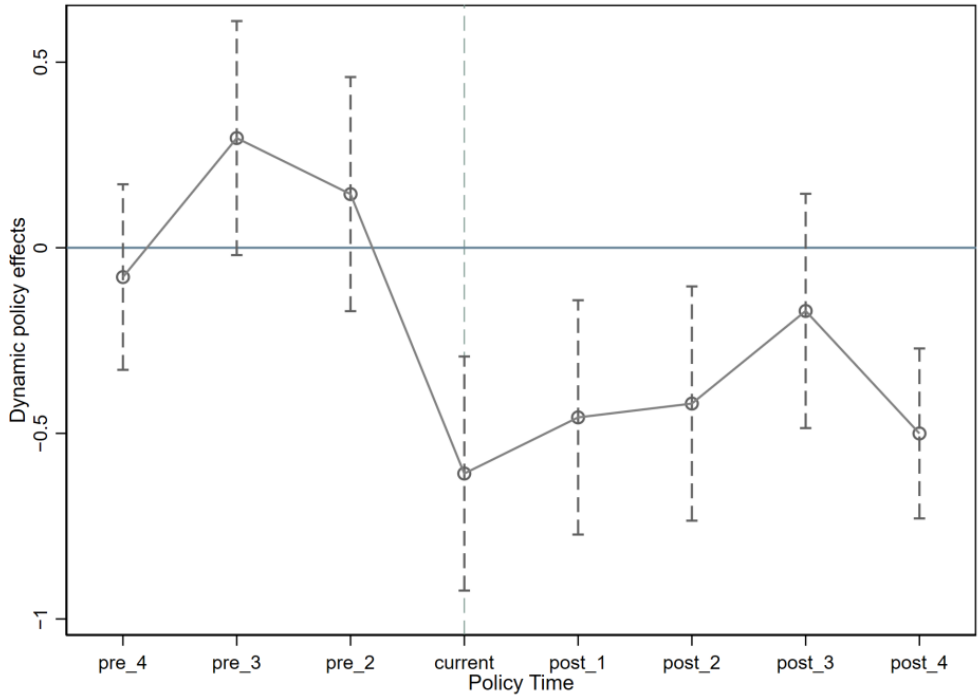

Figure A2. Results of parallel trend hypothesis testing where the explanatory variable is PM10. Note: Data for the pre_1 period is not available in the graph as the first period before the policy shock is used as the base group.

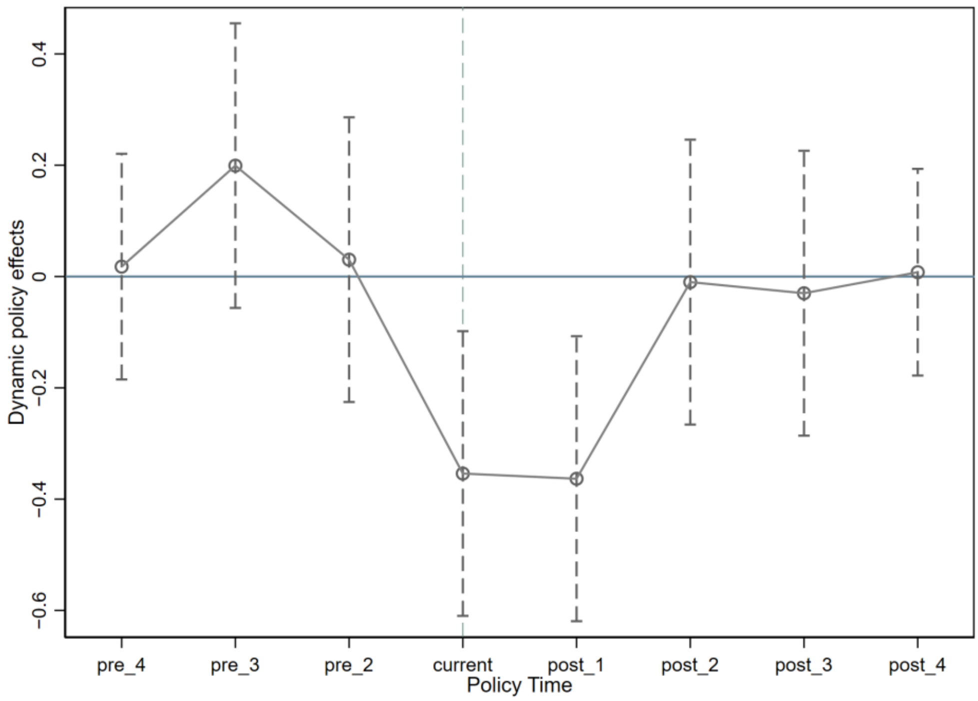

Figure A3. Results of parallel trend hypothesis testing where the explanatory variable is SO_2. Note: Data for the pre_1 period is not available in the graph as the first period before the policy shock is used as the base group.

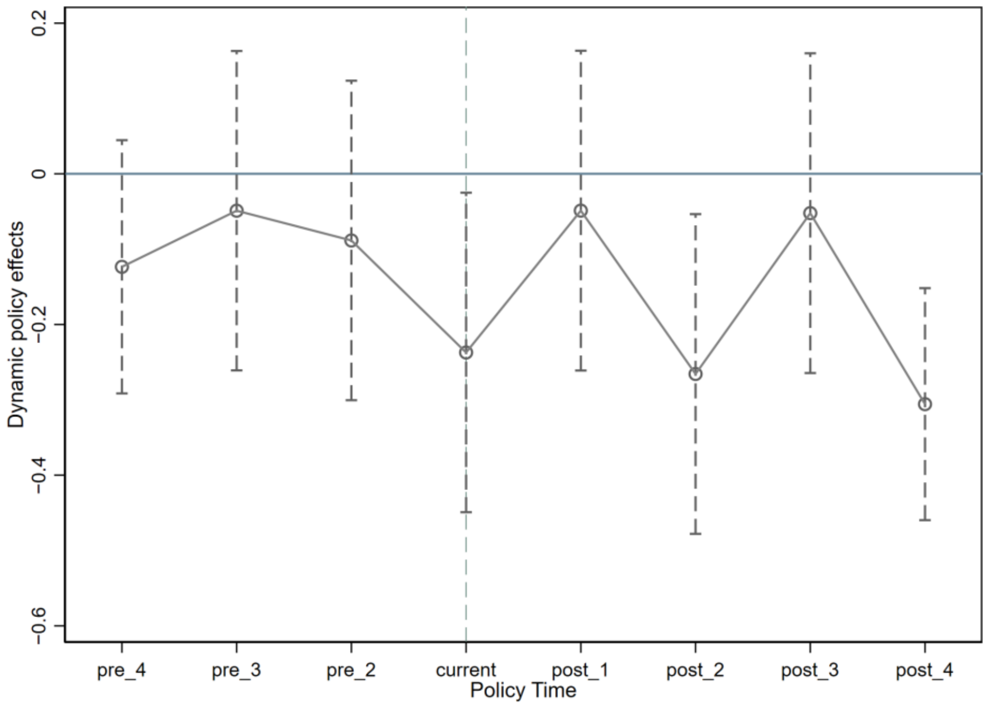

Figure A4. Results of parallel trend hypothesis testing where the explanatory variable is CO. Note: Data for the pre_1 period is not available in the graph as the first period before the policy shock is used as the base group.

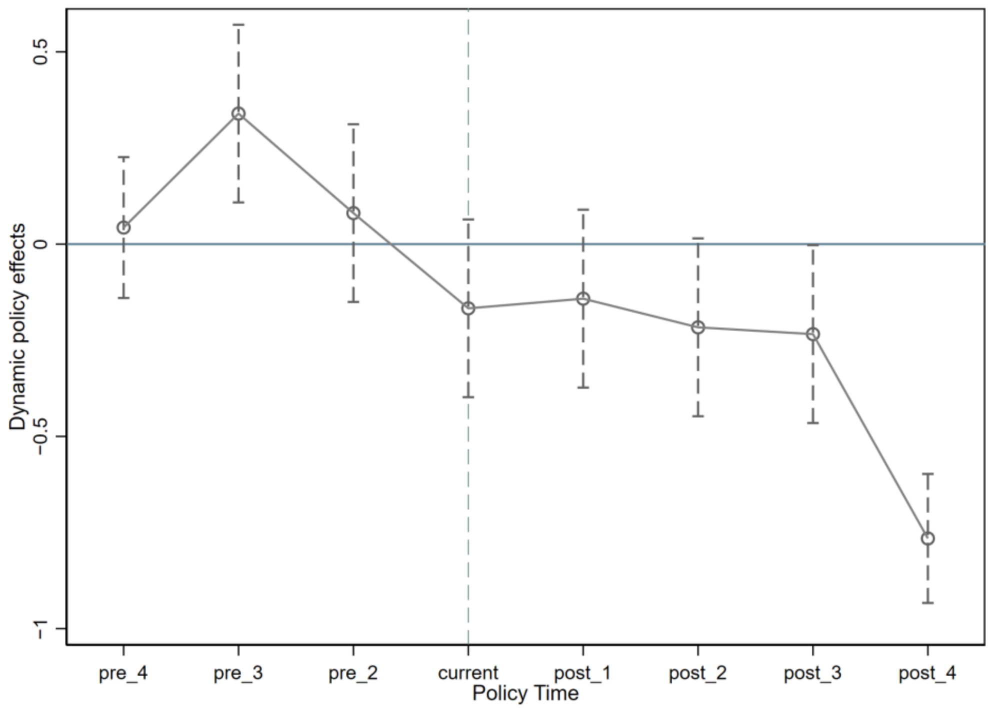

Figure A5. Results of parallel trend hypothesis testing where the explanatory variable is NO_2. Note: Data for the pre_1 period is not available in the graph as the first period before the policy shock is used as the base group.

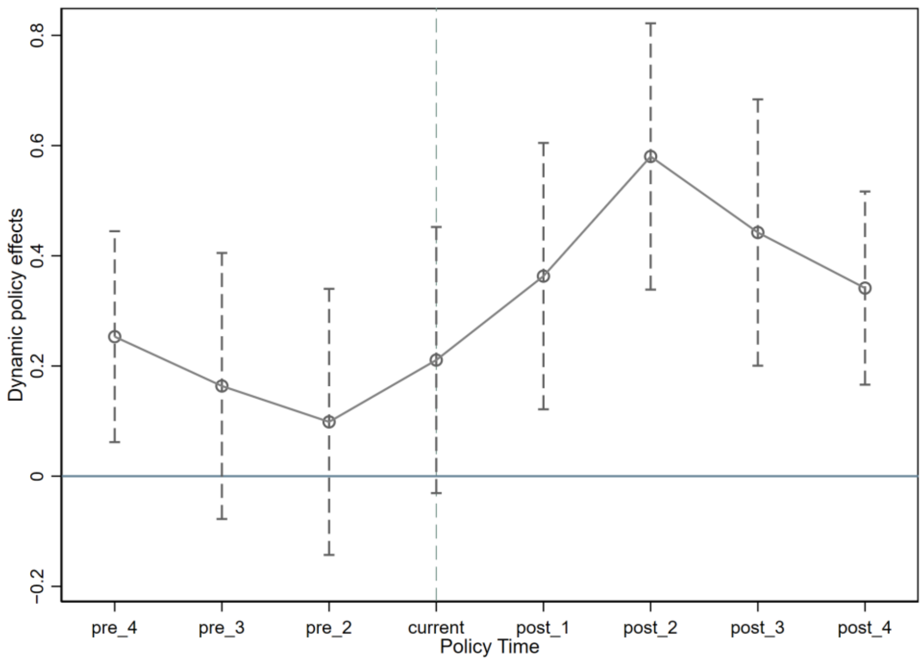

Figure A6. Results of parallel trend hypothesis testing where the explanatory variable is O_3. Note: Data for the pre_1 period is not available in the graph as the first period before the policy shock is used as the base group.

Appendix B

Table A1. A placebo test for causal identification of reduced population movements to improve urban air quality.

	(1) **15 January**	**(2)** **11 January**	**(3)** **8 January**
$treat_i * post_t$	1.038	3.626	−2.036
	(2.210)	(2.376)	(3.287)
Lowest temperature	−0.073	−0.056	−0.091
	(0.248)	(0.250)	(0.246)
Highest temperature	2.684 ***	2.675 ***	2.692 ***
	(0.272)	(0.272)	(0.271)
Wind	−13.883 ***	−13.878 ***	−13.898 ***
	(2.445)	(2.443)	(2.440)
Lowest temperature^2	−0.025 ***	−0.025 ***	−0.025 ***
	(0.009)	(0.009)	(0.009)
Highest temperature^2	−0.005	−0.005	−0.005
	(0.010)	(0.010)	(0.010)
Wind^2	1.157 **	1.157 **	1.159 **
	(0.493)	(0.493)	(0.493)
Constant	120.798 ***	121.021 ***	120.573 ***
	(4.904)	(4.937)	(4.958)
Sample size	17,051	17,051	17,051
R-squared	0.526	0.526	0.526
Time FE	YES	YES	YES
Urban FE	YES	YES	YES

Note: Figures in brackets are clustering robustness criteria errors; **, and *** denote significance levels of 5%, and 1%, respectively.

Appendix C

Table A2. Robustness test—replacing the explanatory variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnAQI	*lnPM*2.5	*lnPM*10	$lnSO_2$	*lnCO*	$lnNO_2$	lnO_3
$treat_i * post_t$	−0.456 ***	−0.594 ***	−0.523 ***	−0.077 *	−0.183 ***	−0.772 ***	0.144 ***
	(0.042)	(0.049)	(0.045)	(0.042)	(0.042)	(0.043)	(0.039)
Lowest temperature	0.007 ***	0.017 ***	0.009 ***	−0.010 ***	0.000	−0.002	−0.013 ***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Highest temperature	0.031 ***	0.030 ***	0.038 ***	0.024 ***	0.023 ***	0.026 ***	0.019 ***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Wind	−0.125 ***	−0.121 ***	−0.180 ***	−0.004	−0.047 **	−0.073 ***	−0.010
	(0.025)	(0.031)	(0.033)	(0.023)	(0.020)	(0.021)	(0.020)
Lowest temperature^2	0.000 ***	0.000 ***	0.001 ***	0.000 **	0.000 **	0.000 ***	−0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highest temperature^2	0.000	0.001 ***	0.000 *	0.000 *	−0.000 ***	0.000	0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wind^2	0.011 **	−0.006	0.025 ***	−0.022 ***	−0.013 ***	−0.026 ***	0.004
	(0.005)	(0.006)	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)
Constant	4.506 ***	4.071 ***	4.427 ***	1.884 ***	−0.212 ***	3.848 ***	3.925 ***
	(0.038)	(0.049)	(0.047)	(0.036)	(0.032)	(0.032)	(0.036)
Sample size	11,804	11,804	11,792	11,804	11,804	11,804	11,804
R-squared	0.662	0.711	0.717	0.798	0.611	0.802	0.492
Time FE	YES	YES	YES	YES	YES	YES	YES
Urban FE	YES	YES	YES	YES	YES	YES	YES

Note: Figures in brackets are clustering robustness criteria errors; *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

Appendix D

Table A3. Robustness test—multi-period DID model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	lnAQI	*lnPM*2.5	*lnPM*10	$lnSO_2$	*lnCO*	$lnNO_2$	lnO_3
D_{it}	−0.448 ***	−0.590 ***	−0.502 ***	−0.067	−0.186 ***	−0.788 ***	0.119 ***
	(0.044)	(0.051)	(0.045)	(0.043)	(0.043)	(0.041)	(0.039)
Lowest temperature	0.007 ***	0.017 ***	0.009 ***	−0.010 ***	0.000	−0.002	−0.013 ***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Highest temperature	0.031 ***	0.030 ***	0.038 ***	0.024 ***	0.023 ***	0.027 ***	0.019 ***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Wind	−0.126 ***	−0.123 ***	−0.181 ***	−0.004	−0.048 **	−0.074 ***	−0.009
	(0.025)	(0.031)	(0.032)	(0.023)	(0.020)	(0.021)	(0.020)
Lowest temperature^2	0.000 ***	0.000 ***	0.001 ***	0.000 **	0.000 **	0.000 ***	−0.000 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Highest temperature^2	0.000	0.001 ***	0.000 *	0.000 *	−0.000 ***	0.000	0.001 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wind^2	0.011 **	−0.006	0.025 ***	−0.022 ***	−0.012 ***	−0.026 ***	0.004
	(0.005)	(0.006)	(0.007)	(0.005)	(0.004)	(0.004)	(0.004)
Constant	4.507 ***	4.071 ***	4.428 ***	1.885 ***	−0.212 ***	3.847 ***	3.923 ***
	(0.038)	(0.049)	(0.047)	(0.036)	(0.032)	(0.032)	(0.036)
Sample size	11,804	11,804	11,792	11,804	11,804	11,804	11,804
R-squared	0.662	0.712	0.717	0.798	0.611	0.803	0.492
Time FE	YES	YES	YES	YES	YES	YES	YES
Urban FE	YES	YES	YES	YES	YES	YES	YES

Note: Figures in brackets are clustering robustness criteria errors; *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively.

References

1. Yuan, Y.; Xu, G.; Chen, X.H.; Jia, J.M. Research on the Interaction Mechanism between Urban Traffic Congestion and Air Pollution-a Big Data Analysis based on DiDi Travel. *J. Manag. Sci.* **2020**, *23*, 54–73.
2. Sun, C.W.; Luo, Y.; Yao, X. Transportation Infrastructure and Urban Air Pollution—Empirical Evidence from China. *Econ. Res.* **2019**, *54*, 136–151.
3. Liang, R.B.; Xi, P.H. Heterogeneous Impact of Rail Transportation on Air Pollution—An Empirical Study based on RDID Method. *China Ind. Econ.* **2016**, *3*, 83–98.
4. Cao, J.; Wang, X.; Zhong, X.H. Has the Traffic Restriction Policy Improved the Air Quality in Beijing? *Econ. Q* **2014**, *13*, 1091–1126.
5. Chester, M.; Horvath, A. High-speed Rail with Emerging Automobiles and Aircraft can Reduce Environmental Impacts in California's future. *Environ. Res. Lett.* **2012**, *7*, 034012.
6. Li, J.M.; Luo, N.S. Has the Opening of High-speed Rail Improved Urban Air Pollution Levels? *Econ. Q* **2020**, *19*, 1335–1354.
7. Xu, W.P.; Jiang, H.; Li, Y.S. A Study on the Differences in Environmental Effects of Population Agglomeration and Economic Agglomeration in China-Analysis based on Provincial Panel Data. *Ecol. Econ.* **2018**, *34*, 123–127.
8. Zhou, S.F.; Zhang, J.J. A Study on the Spatial and Temporal Effects of New Urbanization on Urban Air Pollution in China. *Ind. Technol. Econ.* **2019**, *38*, 66–75.
9. Wang, H.X.; Shi, D.Q. Does New Urbanization Help Alleviate Haze Pollution-Empirical Evidence from Low-carbon City Construction. *J. Shanxi Univ. Financ. Econ.* **2019**, *41*, 15–27.
10. Deng, X.; Zhang, W. Are Large Cities Aggravating Regional Environmental Pollution? *J. Beijing Univ. Technol. (Soc. Sci. Ed.)* **2018**, *20*, 36–44.
11. Guo, S.H.; Gao, M.; Wu, X.P. Economic development, urban expansion and air pollution. *Res. Financ. Econ.* **2017**, *9*, 114–122.
12. Gao, M.; Wu, X.P.; Guo, S.H. Urbanization Process, Environmental Regulation and Air Pollution—An Empirical Analysis based on STIRPAT Model. *Ind. Technol. Econ.* **2016**, *35*, 110–117.
13. Guo, F.; Shi, Q.L. Official Turnover, Collusive Deterrence and Temporary Improvement in Air Quality. *Econ. Res.* **2017**, *52*, 155–168.
14. Huang, R.B.; Zhao, Q.; Wang, L.Y. Natural Resource Asset Separation Audits and Air Pollution Prevention: "Harmony Tournament" or "Environmental Qualification Tournament". *China Ind. Econ.* **2019**, *10*, 23–41.
15. Hu, Y.; Zhang, X.W.; Li, J. Export Trade, Geographical Characteristics and Air Pollution. *China Ind. Econ.* **2019**, *9*, 98–116.
16. Wang, L.; Liu, X.F.; Xiong, Y. Central Environmental Protection Inspectors and Air Pollution Control—An Empirical Analysis based on Micro Panel Data of Prefecture-level Cities. *China Ind. Econ.* **2019**, *10*, 5–22.
17. Shapiro, J.S.; Walker, R. Why is Pollution from US Manufacturing Declining? The Roles of Environmental Regulation, Productivity and Trade. *Am. Econ. Rev.* **2018**, *108*, 3814–3854. [CrossRef]
18. Pandey, A.K.; Singh, S.; Berwal, S.; Kumar, D.; Pandey, P.; Prakash, A.; Lodhi, N.; Maithani, S.; Jain, V.K.; Kumar, K. Spatio—Temporal Variations of Urban Heat Island over Delhi. *Urban Clim.* **2014**, *10*, 119–133.
19. Pandey, A.K.; Rawal, R.S.; Gairola, S.; Bhatt, I.D.; Kumar, R.P.; Priyadarshini, N.; Kumar, A. Protection from Anthropogenic Disturbances Contributed to the Recovery of Vegetation in the Kumaon Himalaya: A Case Study. *Int. J. Geol. Earth Environ. Sci.* **2017**, *7*, 39–50.
20. Sun, W.Z.; Zhang, X.N.; Zheng, S.Q. Air Pollution and Spatial Mobility of Labor Force—A Study based on the Employment Location Selection Behavior of Mobile Population. *Econ. Res.* **2019**, *54*, 102–117.
21. Zhang, H.F.; Lin, X.X.; Liang, R.B.; Lan, J.J. Urban Ecological Civilization Construction and New Generation of Labor Mobility—A New Perspective on Labor Resource Competition. *China Ind. Econ.* **2019**, *4*, 81–97.
22. Xi, P.H.; Liang, R.B. Urban Air Quality and Environmental Migration—An Empirical Study based on Fuzzy Breakpoint Model. *Econ. Sci.* **2015**, *4*, 30–43.
23. Li, M.; Zhang, Y.R. The Migration Effect of Air Pollution—A Study based on the University-city Choice of Incoming Students. *Econ. Res.* **2019**, *54*, 168–182.
24. Menut, L.; Bessagnet, B.; Siour, G.; Mailler, S.; Pennel, R.; Cholakian, A. Impact of Lockdown Measures to Combat COVID-19 on Air Quality over Western Europe. *Sci. Total Environ.* **2020**, *741*, 140426. [PubMed]
25. He, G.J.; Pan, Y.H.; Tanaka, T. The Short-term Impacts of COVID-19 Lockdown on Urban Air Pollution in China. *Nat. Sustain.* **2020**, *3*, 1005–1011. [CrossRef]
26. Pei, Z.P.; Han, G.; Ma, X.; Su, H.; Gong, W. Response of Major Air Pollutants to COVID-19 Lockdowns in China. *Sci. Total Environ.* **2020**, *743*, 140879. [CrossRef] [PubMed]
27. Yang, Z.; Chen, Y.T.; Zhang, P.M. Macroeconomic Shocks, Financial Risk Transmission and Governance Responses under Major Public Emergencies. *Manag. World* **2020**, *36*, 13–35+7.
28. Jiang, H.; Liu, Y. A Comparison of the Economic Effects of Trade Frictions between China and the United States before and after the Outbreak of the New Crown Pneumonia Outbreak. *World Econ. Political Forum* **2021**, *3*, 54–77.
29. Tan, P.H.; Chou, C.; Liang, J.Y.; Charles, C.; Shiu, C.J. Air Pollution "Holiday Effect" Resulting from the Chinese New Year. *Atmos. Environ.* **2009**, *43*, 2114–2124.
30. Almond, D.; Du, X.; Zhang, S. Ambiguous Pollution Response to COVID-19 in China. *NBER Work. Pap.* **2020**. [CrossRef]
31. Fang, H.M.; Wang, L.; Yang, Y. Human Mobility Restrictions and the Spread of the Novel Coronavirus (2019-nCoV) in China. *J. Public Econ.* **2020**, *191*, 104272. [PubMed]

32. Luo, Z.; Zhao, Q.W.; Yan, B. The Impact of Constraint Mechanism and Incentive Mechanism on Long-term Investment of State-owned Enterprises. *China Ind. Econ.* **2015**, *10*, 69–84.
33. Wang, T.; Xue, L.K.; Brimblecombe, P.; Lam, Y.F.; Zhang, L. Ozone Pollution in China: A Review of Concentrations, Meteorological Influences, Chemical Precursors and Effects. *Sci. Total Environ.* **2016**, *575*, 1582–1596. [PubMed]
34. Li, K.; Jacob, D.J.; Liao, H.; Shen, L.; Zhang, Q.; Bates, K.H. Anthropogenic Drivers of 2013–2017 Trends in Summer Surface Ozone in China. *Proc. Natl. Acad. Sci. USA* **2019**, *116*, 422–427. [CrossRef] [PubMed]
35. Lv, Z.; Wang, X.; Deng, F.; Ying, Q.; Archibald, A.T.; Jones, R.L.; Ding, Y.; Cheng, Y.; Fu, M.; Liu, Y.; et al. Significant Reduced Traffic in Beijing Failed to Relieve Haze Pollution during the COVID-19 Lockdown: Implications for Haze Mitigation. *arXiv* **2020**, arXiv:2006.07297.