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Original Paper

Impact of Lockdown on Air Pollution: Evidence from the “2+26” Cities in the Beijing-Tianjin-Hebei Region

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Abstract

To prevent the spread of COVID-19 in China, many cities were locked down after January 23, 2020. Based on the panel data of the “2+26” cities from 10 January to 15 March 2020, this paper took the lockdown as a quasi-natural experiment and established a multi-phase DID model to investigate whether the lockdown measures significantly reduced air pollution in locked-down cities in the Beijing-Tianjin-Hebei (BTH) region. The core innovation of this paper is that we considered the urban immigration scale index as a mediating variable , which is rarely adopted in the existing literature, and we identified the relationships between the lockdown, the intracity migration index, the urban immigration scale index and air pollution. The results showed that compared with the non-locked-down cities, the lockdown significantly reduced air pollution. Furthermore, it was found that the lockdown reduced air pollution by reducing intracity migration and the urban scale of immigration. Moreover, compared with the corresponding period in 2019, air pollution was significantly reduced in the locked-down cities of the “2+26” cities. Air pollution is closely related to human activity, and green production and technological innovations are critical for reducing air pollution in the BTH region.

Keywords

lockdown, air pollution, intracity migration, urban immigration scale, DID model

1. Introduction

In December 2019, a novel coronavirus (COVID-19) epidemic broke out in Wuhan, China and spread throughout the country and the world. To prevent the spread of COVID-19, the Chinese government took immediate and decisive action; as such, Wuhan was locked down on 23 January 2020. In the next 10 days, 95 cities were locked down (He et al., 2020). Those in Wuhan had to live in quarantine, stop production and cancel all gathering activities. The lockdown has caused huge losses in the entire economy and society. However, due to the suspension of social development that was caused by the lockdown, the air quality was expected to improve greatly during this period in China. Furthermore, compared with non-locked-down cities, the lockdown measures were expected to reduce air pollution.

Because of its rapid development, China has been suffering severe air pollution problems for a long time, where its air quality ranking has always been low (Wendling et al., 2018). According to the Ministry of Ecology and Environment of the People's Republic of China, the "2+26" cities are the main cities in the pollution transmission channels. These include Beijing, Tianjin, Shijiazhuang, Tangshan, Langfang, Baoding, Cangzhou, Hengshui, Xingtai and Handan in Hebei Province; Taiyuan, Yangquan, Changzhi and Jincheng in Shanxi Province; Jinan, Zibo, Jining, Dezhou, Liaocheng, Binzhou and Heze in Shandong Province; Zhengzhou, Kaifeng, Anyang, Hebi, Xinxiang, Jiaozuo and Puyang in Henan Province. These cities are located in northern China, with a total area of 270,000 km2, accounting for 2.9% of the total area of China. The specific location is shown in Figure 1. The "2+26" cities are among the most economically developed regions in China. According to the China City Statistical Yearbook 2020, in 2019, the total population of these 28 cities was 190 million, accounting for about 14% of the national population. At the same time, the GDP was 14 trillion CNY, accounting for about 14% of China's total GDP. In 2017, the Ministry of Environmental Protection issued "The '2+26' Cities Around BTH Region Air Pollution Prevention and Control Work Plan in 2017", which identified the "2+26" cities in the air pollution transmission channel that needed to effectively improve their air quality and published an action plan for the comprehensive management of air pollution in autumn and winter every year to promote the improvement of the regional air quality in these cities. At the same time, the Ministry of Ecology and Environment listed the "2+26" cities as some of the key areas for national air quality improvement and focused on analyzing the air quality every month. In 2020, the "2+26" cities had an average of 63.5% of good days and a PM2.5 concentration of 51 μg/m3. The average number of good air days (Days meet China's ambient air quality standards (GB3095-2012)) in 337 cities across China was 87.0%, and the average PM2.5 concentration was 33 μg/m3. The air quality in the "2+26" cities was markedly lower than the national average. Meanwhile, the air quality reports of 168 key cities in 2020 showed that among the 20 cities with the worst air quality, 15 cities were from the "2+26" cities. This shows that this region is still a key polluted area and thus the air quality urgently needs to continue to improve. BTH region is the "capital economic circle" of China, the largest and most dynamic region in northern China, as well as one of the three most economically developed regions in China (Zhang et al., 2021). Therefore, we regarded this area as the study area.

Figure 1. Geographical Location of the "2+26" Cities

The locked-down and non-locked-down cities in the "2+26" cities are shown in Table 1.

Table 1. Locked-down and Non-Locked-down Cities around the BTH Region

locked-down cities	non-locked-down cities
Beijing, Tianjin, Shijiazhuang, Cangzhou, Tangshan, Jinan, Jining, Zhengzhou	Baoding, Handan, Hengshui, Langfang, Xingtai, Taiyuan, Changzhi, Jincheng, Yangquan, Zibo, Dezhou, Liaocheng, Binzhou, Heze, Kaifeng, Anyang, Hebi, Xinxiang, Jiaozuo, Puyang

The nationwide lockdown can be considered as an ideal and unique field experiment for the prevention and control of the current severe air pollution (Wang & Zhang, 2020). Therefore, this study took the lockdown as a quasi-natural experiment. A multi-phase DID model was applied to conduct our analysis and the mediating effect test model is established to investigate the micro-mechanism of the reduction in air pollution.

Many studies demonstrated that emergencies or policy measures, such as air pollution control during the Beijing Olympic Games (He et al., 2016) and APEC meetings (Li et al., 2017), and the 2008-2009 global economic recession (Castellanos & Boersma, 2012; Tong et al., 2016), can significantly reduce air pollution. Could the lockdown measures against the COVID-19 pandemic have reduced air pollution and improved the environmental quality? The drastic drop in air pollutant emissions that occurred with the national lockdown greatly improved the human living environments (Kasha Patel, 2020). Compared with the same period last year, China's carbon emissions decreased by 9.8% in the first quarter of 2020, and other air pollutant indicators also declined (Yue Xu et al., 2020). Within a few weeks after the lockdown, AQI and PM2.5 both decreased by 25%, and in the cold, affluent and more industrialized cities, the pollutant indicators decreased more significantly (He et al., 2020). It was shown that a partial limitation helped to improve the air quality during the COVID-19 pandemic in

Beijing (Tao et al., 2021). The air quality index (AQI) significantly decreased by 20.56, and the emission concentrations of the pollutants PM2.5, PM10, and NO2 decreased by 19.01, 20.20, and 2.13, respectively (Song et al., 2021). To accurately analyze the impact of lockdown on air quality, some studies used monitoring data to conduct their research. Based on the data generated by the 1641 operational stations of China's National Environmental Monitoring Center, Shi and Brasseur (Shi & Brasseur, 2020) found that the average level of PM2.5 and NO2 at the surface decreased by approximately 35 and 60% respectively between 23 January and 29 February 2020. In the Yangtze River Delta Region, SO2, NOx, PM2.5 and VOCs decreased by approximately 16-26, 29-47, 27-46 and 37-57%, respectively, which effectively improved the air quality in this region (Li et al., 2020). The lockdown during the COVID-19 pandemic improved the air quality in many other countries. Based on ground and satellite observation data, Singh and Chauhan (Singh & Chauhan, 2020) found that India's PM2.5 and NO2 concentrations decreased significantly because of the lockdown, which began on 22 March 2020. Kumari and Toshniwal (Kumari & Toshniwal, 2020) analyzed data from 162 monitoring stations in 12 cities around the world and found that the concentrations of PM2.5, PM10 and NO2 all decreased. In Greece, the lockdown resulted in a significant drop in PM2.5 by 37.4% in 2020 compared with 2019 levels (Kotsiou et al., 2021).

Several other studies took the lockdown as a quasi-natural experiment, using the traditional Difference-in-Differences (DID) approach to analyze the impact of lockdown on the air quality in China. Compared with 2019, the epidemic prevention measures improved the air quality of the examined cities in 2020 (Chen et al., 2020). Prevention measures also caused China's PM2.5 and AQI to drop by 7 μg /m3 and 5%, respectively (Ming et al., 2020).

Therefore, we proposed the following research hypothesis (H1): The lockdown against the COVID-19 pandemic significantly reduced air pollution.

Industrial production and transportation activities generated and exacerbated air pollution (Shahbazi et al., 2014; Chen et al., 2021), but the private vehicle restriction policies caused a decline in automobile exhaust emissions and slowed down air pollution (Chen et al., 2021). Thus, the suspension of production and transportation during the COVID-19 pandemic may have improved the air quality. The reduction in traffic and human mobility may be reflected by the change in intracity migration, especially the restriction on intracity travel intensity, which had a significant heterogeneous effect on NO2 (Wang et al., 2021). Furthermore, during the lockdown period, people, such as tourists, workers and students, were isolated at home, and thus the reduction in the intracity migration index also greatly reduced urban air pollution (Bao & Zhang, 2020; Li et al., 2020). The traffic restrictions and reduction in human movement had an obvious effect on air quality.

Therefore, we proposed our second research hypothesis (H2): The lockdown reduced air pollution by reducing the intracity migration index and the scale of urban immigration.

The contribution of this study is threefold: First, we used a multi-period DID model to study the impact of the lockdown on urban air pollution. The existing literature mostly used the traditional DID model or monitoring station data to directly analyze air pollution during the COVID-19 pandemic period, but few studies used the multi-phase DID model. Second, we used the mediating effect test model to explore the micro-mechanisms of the impact of the lockdown on air pollution from the aspects of the intracity migration index and the urban immigration scale index. Unlike the existing research, which mostly studied the impact of the lockdown or intracity migration index on air pollution, we identified the relationships between the lockdown, the intracity migration index, the urban immigration scale index and air pollution. Furthermore, no research was found that considered the urban immigration scale index as a mediating variable. Therefore, this study established a mediating effect test model to explore how the intracity migration index and the urban immigration scale index affected air pollution. Third, we focused on a comparative analysis, not only comparing the locked-down cities with the non-locked-down, but also compared them with the same period in 2019 without the COVID-19 pandemic. In this study, we conducted a comprehensive analysis of the impact of the lockdown on air pollution and its micro-mechanisms.

2. Materials and Data

2.1 Study Tool

This study mainly used the DID model to calculate the specific effect of the lockdown on reducing air pollution and used the mediating effect test model to calculate the impact of the lockdown on air pollution through intracity migration index and the urban immigration scale index. The main tool used was Stata15.

2.2 Data Sources

This research was conducted on the panel data of the “2+26” cities from 10 January to 15 March in 2020. Taking 8 locked-down cities in the “2+26” cities as the treatment group and the other 20 non-locked-down cities as the control group, we obtained 1848 valid data values. The lockdown period data came from news media, government policy documents and the work of He et al. (He et al., 2020). The urban air pollution and weather condition data came from the data center of the Ministry of Ecology and Environment (https://air.cnemc.cn:18007/) and the online air quality monitoring platform (https://www.aqistudy.cn/). The intracity migration index and the urban immigration scale index data came from the Baidu migration website (http://qianxi.baidu.com/).

2.3 Variables

2.3.1. Dependent Variable

Air pollution can be measured using the air quality index (AQI) and six types of air pollutants: $PM_{2.5}$, PM_{10}, CO, SO_2, NO_2 and O_3. Thus, this study selected the AQI and the six air pollutants to reflect the dependent variable, namely, air pollution.

The AQI is calculated via the following method:

$$AQI = \max\left\{IAQI_1, IAQI_2, \cdots, IAQI_n\right\}$$

$$IAQI_p = \frac{IAQI_{Hi} - IAQI_{Lo}}{BP_{Hi} - BP_{Lo}}(C_p - BP_{Lo}) + IAQI_{Lo}$$

where $IAQI_p$ is the air quality sub-index of the pollutant items SO_2, NO_2, CO, O_3 and air particulate matter; C_p is the concentration value of the pollutant items SO_2, NO_2, CO, O_3 and air particulate matter; BP_{Hi} is the high value of the pollutant concentration limit close to C_p; BP_{Lo} is the low value of the pollutant concentration limit close to C_p; $IAQI_{Hi}$ is the air quality index corresponding to BP_{Hi}; and $IAQI_{Lo}$ is the air quality index corresponding to BP_{Lo}.

2.3.2 Independent Variable

The central independent variable is the interaction term of the time and policy dummy variable for city i in period t. The policy dummy variable equals 1 if a city was locked down; otherwise, it equals 0. For locked-down cities, the time dummy variable equals 1 for the time after the lockdown; otherwise, it equals 0.

2.3.3 Control Variable

Weather conditions have an important impact on air pollution (Yen et al., 2013); therefore, motivated by the control variables selected in (Bao & Zhang, 2020; He et al., 2020), this study selected temperature, humidity and wind speed as the control variables.

Air temperature is the average daily temperature, expressed in degrees Celsius; Humidity is the degree of dryness and wetness in the air, taken from relative humidity data and expressed as a percentage. Wind speed represents the average daily wind speed, expressed in meters per second.

2.3.4 Mediating Variables

Lockdown mainly impact air pollution by reducing human mobility. The intracity migration index is the ratio of the number of people traveling to the resident population in the city, and the urban immigration scale index is the population that moved into the city. Both variables can reflect population mobility. We thus selected the intracity migration index and the urban immigration scale index to measure population mobility.

The descriptions and abbreviations of the main variables are shown in Table 2.

Table 2. Descriptions and Abbreviations of the Main Variables

Variable	Description	Abbreviation
natural logarithm of air quality index	air pollution measurement	lnAQI
natural logarithm of $PM_{2.5}$		$lnPM_{2.5}$

natural logarithm of PM_{10}		$lnPM_{10}$
natural logarithm of CO		lnCO
natural logarithm of SO_2		$lnSO_2$
natural logarithm of NO_2		$lnNO_2$
natural logarithm of O_3		lnO_3
whether or not lockdown	after lockdown, equals to 1, otherwise equals to 0	time
whether or not the city is lockdown city	lockdown city, equals to 1, otherwise equals to 0	treat
the dummy variable that city i is treated at period t	the interaction term of time and treat	lockdown
temperature (unit: Celsius)	weather condition	temper
humidity (unit: %)		humidity
wind level (unit: m/s)		wind
the intracity migration index	measure human mobility	travelden
the urban immigration scale index		immigrate

2.4 Descriptive Statistics

The descriptive statistics of the main variables are shown in Table 3.

Table 3. Descriptive Statistics

lockdown cities				
Variables	Mean	Standard deviation	Minimum	Maximum
lnAQI	4.505	0.561	3.434	5.759
$lnPM_{2.5}$	4.069	0.787	1.099	5.587
$lnPM_{10}$	4.385	0.669	2.079	5.932
lnCO	-0.0321	0.552	-1.609	2.001
$lnSO_2$	2.327	0.632	0.693	4.248
$lnNO_2$	3.426	0.528	1.609	4.605
lnO_3	4.239	0.399	2.565	4.927
temper	3.307	4.378	-6.792	16
humidity	60.14	17.19	17.42	97.50
wind	1.906	0.764	0.708	5.583
travelden	3.235	1.459	0.925	6.640
immigrate	1.735	1.693	0.184	12.15
non-lockdown cities				

Variables	Mean	Standard deviation	Minimum	Maximum
lnAQI	4.572	0.530	3.466	6.071
$\ln PM_{2.5}$	4.163	0.715	1.792	5.989
$\ln PM_{10}$	4.552	0.565	2.708	6.089
lnCO	0.0222	0.502	-1.609	1.609
$\ln SO_2$	2.499	0.571	0.693	4.143
$\ln NO_2$	3.346	0.507	1.792	4.554
$\ln O_3$	4.281	0.379	2.398	4.970
temper	3.395	4.291	-9.500	16.25
humidity	62.51	19.10	15.63	100
wind	1.708	0.613	0.458	4.667
travelden	3.398	1.445	1.160	6.546
immigrate	0.680	0.710	0.0232	4.379

Table 3 shows that, compared with non-locked-down cities, the average values of the air pollution indicators and intracity migration index in locked-down cities are lower, while the average value of the urban immigration scale index is slightly higher. Specifically, compared with non-locked-down cities, the AQI and travelden of locked-down cities are 0.067 and 0.163 lower than the average, respectively. The urban immigration scale index is 1.055 higher than the average. Overall, there were large differences between the maximum and minimum values of the dependent variable (air pollution), and the standard deviation was also larger, that is 2.325 and 0.561, which indicates that the air pollution in different cities varied considerably. Moreover, the differences between the maximum and minimum values of the mediating variables (the intracity migration index and the urban immigration scale index) were also large, which indicates large differences between different cities. However, further empirical research should be conducted to explore the relationships between these three variables.

3. Empirical Model and Analysis

3.1 Introduction of the DID Model

DID is a method that is used to test the effectiveness of a policy, which can estimate the net impact of a certain policy on the treatment group. The specific idea is to use the sample affected by the policy as the treatment group and the sample not affected by the policy as the control group. The net impact of the policy can be obtained by the difference between the average change in the treatment group and the average change in the control group. The model used for this study can be expressed as:

$$Y_{it} = \beta_0 + \beta_1 G_i * D_t + \beta_2 G_i + \beta_3 D_t + \beta_4 X + \varepsilon_{it} \qquad (1)$$

Where Y_{it} represents the explanatory variable i in period t and G_i is the treatment group dummy variable. If i belongs to the treatment group, G_i equals 1; otherwise, it equals 0. D_t is the time dummy variable which equaled 1 if the time was after the policy started; otherwise, it equaled 0. The coefficient β_1 is the impact of implementing policy on the explanatory variable. As shown in the Table 4, the difference was $\beta_1+\beta_2$ after the policy started, and the difference was β_2 before the policy started. The difference after the policy started was subtracted from the difference before the policy to obtain the double difference result of β_1. ε_{it} is the stochastic error term.

Table 4. Principles of the DID Model

	Before the policy started	After the policy started	
Treatment group	$\beta_0+\beta_2$	$\beta_0+\beta_1+\beta_2+\beta_3$	
Control group	β_0	$\beta_0+\beta_3$	
Difference	β_2	$\beta_1+\beta_2$	β_1

3.2 Parallel Trend Test Model

This study mainly used the DID model to investigate the impact of the lockdown on air pollution. An important assumption of the DID model is that the treatment group and the control group had a common trend before the policy implementation, which means that the dependent variable (air pollution) should have had the same trend in the treatment and the control group before lockdown. Therefore, it is necessary to conduct a parallel trend test. Based on the event study in (Chen et al., 2020), this study established a parallel trend test model as follows:

$$\ln Y_{it}=\beta_0+\beta_1 treat*pre+\beta_2 \mathrm{treat}*\mathrm{current}+\beta_3 treat*post+\beta_4 X+\alpha_i+\lambda_t+\varepsilon_{it} \quad (2)$$

where $treat$ is a dummy variable that equaled 1 when the city was locked down and 0, otherwise; pre is also a dummy variable, which equaled 1 for the current period and 0 for the period before the lockdown; $current$ is a dummy variable, which equaled 1 for the lockdown period and equaled 0, otherwise; $post$ is a dummy variable, which equaled 1 for the current period and 0 for the period after the lockdown. X represents control variables, such as temperature, humidity and wind level, which impact air pollution; α_i is the time fixed effect; and λ_t is the time trend item. The coefficient β_1 is the difference in air pollution between cities before the lockdown. If it converges to 0 or is not significant, then the treatment and control groups had a common trend before the lockdown. If β_2 and β_3 are significant, the lockdown had a marked impact on air pollution.

Based on the panel data of the “2+26” cities from 10 January to 15 March, we took lnAQI, lnPM$_{2.5}$, lnPM$_{10}$, lnCO, lnNO$_2$, and lnSO$_2$ as the dependent variables to regress model (1), and the parallel trend was verified using the relationship between the coefficient of policy time and 0. Figures 2-4 show the changes in specific regression coefficients over time.

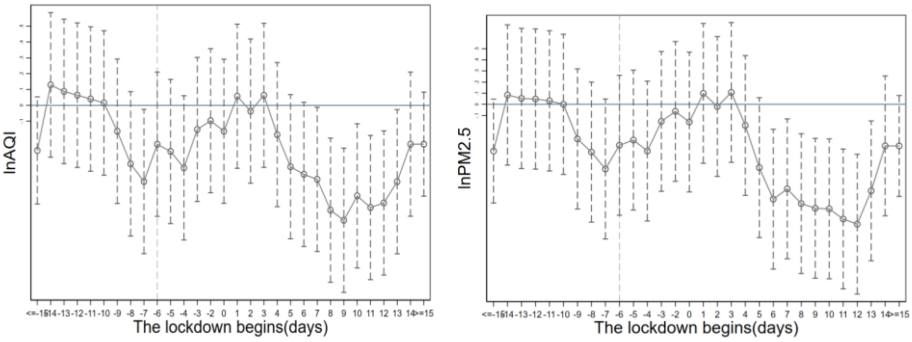

Figure 2. Dynamic Effects of the Lockdown on lnAQI and lnPM$_{2.5}$

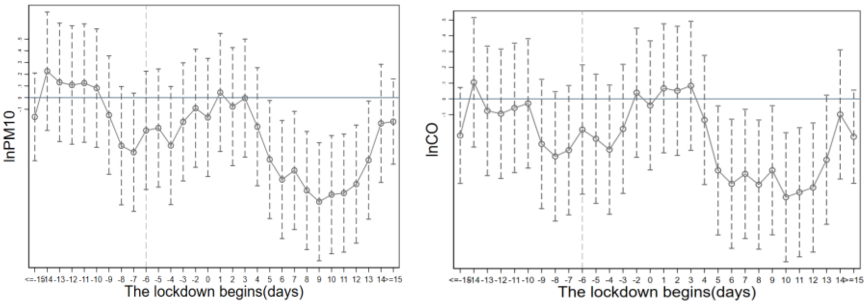

Figure 3. Dynamic Effects of the Lockdown on lnPM10 and lnCO

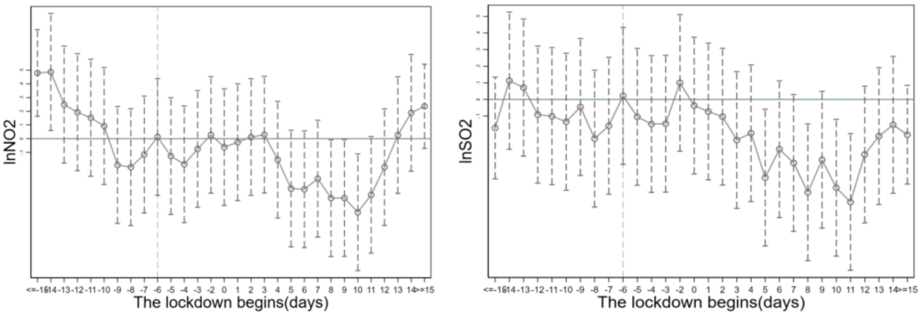

Figure 4. Dynamic Effects of the Lockdown on lnNO$_2$ and lnSO$_2$

Figures 2-4 show that the coefficient β_1 mainly fluctuated around 0 before the lockdown, which means that the treatment group and the control group had the same air pollution trend, i.e., there was a common trend between the treatment group and the control group before the lockdown. The coefficient β_1 changed significantly after the lockdown, which means that the lockdown had a significant impact on air pollution.

3.3 Multi-Phase DID Model

The DID model was used to evaluate the policy's effectiveness, where the sample was divided into a treatment group and a control group to obtain the net impact of policy implementation on the treatment group. Since the start times of the policy in the treatment group were inconsistent, we needed to use the multi-phase DID model. As such, in this study, we established a multi-phase DID model as follows:

$$\ln Y_{it} = \beta_0 + \beta_1 lockdown_{it} + \beta_2 X + \alpha_i + \lambda_t + \varepsilon_{it} \tag{3}$$

where $\ln Y_{it}$ represents the air pollution during period t in city i; $lockdown_{it}$ is the interaction term of $time$ and $treat$, which means that city i was treated (the lockdown had begun) at period t, where $lockdown_{it}$ equaled 1 after the lockdown and 0, otherwise; and β_1 represents the impact of the lockdown on air pollution, where if β_1 is significantly negative, the lockdown significantly reduced the air pollution of the locked-down cities. The other variables are the same as in model (2).

Based on the panel data of the "2+26" cities from 10 January to 15 March, we regressed model (2). The results of the regression are shown in Table 5.

Table 5. Basic Regression Results

VARIABLES	(1) lnAQI	(2) $\ln PM_{2.5}$	(3) $\ln PM_{10}$	(4) lnCO	(5) $\ln NO_2$	(6) $\ln SO_2$
lockdown	-0.167^{***}	-0.271^{***}	-0.279^{***}	-0.132^{***}	-0.170^{***}	-0.120^{***}
	(0.0361)	(0.0447)	(0.0426)	(0.0317)	(0.0399)	(0.0388)
temper	0.0360^{***}	0.0503^{***}	0.0548^{***}	0.0260^{***}	0.0360^{***}	0.0188^{***}
	(0.00299)	(0.00370)	(0.00353)	(0.00263)	(0.00331)	(0.00322)
humidity	0.0158^{***}	0.0250^{***}	0.0153^{***}	0.0141^{***}	0.00399^{***}	-0.00605^{***}
	(0.000546)	(0.000677)	(0.000645)	(0.000480)	(0.000604)	(0.000588)
wind	-0.175^{***}	-0.277^{***}	-0.201^{***}	-0.194^{***}	-0.361^{***}	-0.285^{***}
	(0.0190)	(0.0236)	(0.0224)	(0.0167)	(0.0210)	(0.0204)
Constant	4.135^{***}	3.332^{***}	4.142^{***}	-0.259^{***}	3.909^{***}	3.634^{***}
	(0.0545)	(0.0675)	(0.0643)	(0.0479)	(0.0603)	(0.0586)

city fixed	Y	Y	Y	Y	Y	Y
time trend	Y	Y	Y	Y	Y	Y
Observations	1848	1848	1846	1848	1848	1848
R-squared	0.531	0.612	0.437	0.579	0.318	0.309
Number of id	28	28	28	28	28	28

Columns (1)-(6) are the results of the impact of the lockdown on air pollution with the control variables. Since this study explored whether the lockdown reduced air pollution, the result was not converted into an absolute value and was directly expressed as a negative number, which intuitively illustrates the reduction in air pollution due to the lockdown. Meanwhile, due to the large absolute values of data and the large gap between data samples, this study used logarithms for the regression, which reduced the absolute value of the data, facilitated calculation and interpretation, made the data more stable and weakened heteroscedasticity. At the same time, taking logarithms did not change the relative relationships of the variables. Table 5 showed that the coefficient β_1 was significantly negative at the 1% level, and that, compared with the non-locked-down cities, the AQI, $PM_{2.5}$, PM_{10}, CO, NO_2 and SO_2 of the locked-down "2+26" cities deceased by 16.7, 27.1, 27.9, 13.2, 17.0 and 12.0% on average, respectively. Therefore, we can see that the lockdown reduced the air pollution in the locked-down cities, and thus hypothesis H1 was verified.

3.4 Mediating Effect Test Model

To verify the previous assumption that the lockdown reduced urban air pollution by reducing the intracity migration index and the urban immigration scale index, we established the mediating effect test model as follows:

$$\ln Y_{it} = \beta_0 + \beta_1 lockdown_{it} + \beta_2 X + \alpha_i + \lambda_t + \varepsilon_{it} \tag{4}$$

$$M_{it} = \theta_0 + \theta_1 lockdown_{it} + \theta_2 X + \alpha_i + \lambda_t + \varepsilon_{it} \tag{5}$$

$$\ln Y_{it} = \mu_0 + \mu_1 lockdown_{it} + \mu_2 M_{it} + \mu_3 X + \alpha_i + \lambda_t + \varepsilon_{it} \tag{6}$$

where M_{it} indicates the mediating variables $travelden_{it}$ and $immigrate_{it}$, and the other variables are the same as in model (2). If β_1, θ_1 and μ_2 are significant, this means that the lockdown reduced urban air pollution by reducing the intracity migration index and the urban immigration scale index. Therefore, hypothesis H2 holds and the mediating effect is $\theta_1 * \mu_2$.

Based on the time series of the intracity migration index and the urban immigration scale from 10 January to 15 March 2020, we could find the impact of the lockdown on traffic. Figure 5 presents the specific trends.

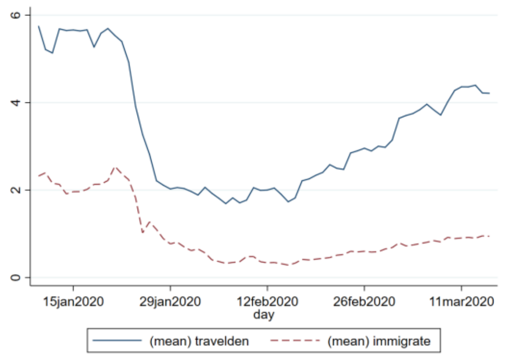

Figure 5. Trends of the Intracity Migration Index and the Urban Immigration Scale Index

As shown in Figure 5, after the lockdown, the intracity migration index and the urban immigration scale index decreased significantly, especially the intracity migration index. Therefore, we could initially infer that the lockdown reduced the intracity migration index and the urban immigration scale index, and thus reduced air pollution. We conducted further empirical analysis, as described in the following paragraph.

Based on the data of 28 cities around the BTH region, we regressed models (4)-(6); the regression results are shown in Tables 6 and 7.

Table 6. Mediating Effect Test: The Intracity Migration Index

Panel A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	travelden	lnAQI	lnAQI	lnPM$_{2.5}$	lnPM$_{2.5}$	lnPM$_{10}$	lnPM$_{10}$
lockdown	-0.617***	-0.167***	-0.131***	-0.271***	-0.241***	-0.279***	-0.214***
	(0.131)	(0.0361)	(0.0355)	(0.0447)	(0.0445)	(0.0426)	(0.0405)
travelden			0.0574***		0.0494***		0.105***
			(0.00631)		(0.00791)		(0.00720)
temper	0.0290***	0.0360***	0.0343***	0.0503***	0.0489***	0.0548***	0.0519***
	(0.0109)	(0.00299)	(0.00293)	(0.00370)	(0.00367)	(0.00353)	(0.00335)
humidity	-0.00127	0.0158***	0.0159***	0.0250***	0.0251***	0.0153***	0.0154***
	(0.00199)	(0.000546)	(0.000535)	(0.000677)	(0.000670)	(0.000645)	(0.000610)
wind	-0.238***	-0.175***	-0.161***	-0.277***	-0.265***	-0.201***	-0.176***
	(0.0692)	(0.0190)	(0.0187)	(0.0236)	(0.0234)	(0.0224)	(0.0213)
Constant	4.583***	4.135***	3.872***	3.332***	3.106***	4.142***	3.660***
	(0.198)	(0.0545)	(0.0607)	(0.0675)	(0.0760)	(0.0643)	(0.0692)
city fixed	Y	Y	Y	Y	Y	Y	Y
time trend	Y	Y	Y	Y	Y	Y	Y
Observations	1848	1848	1848	1848	1848	1846	1846

R-squared	0.124	0.531	0.551	0.612	0.620	0.437	0.496
Number of id	28	28	28	28	28	28	28

Panel B	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	lnCO	lnCO	$\ln NO_2$	$\ln NO_2$	$\ln SO_2$	$\ln SO_2$
lockdown	-0.132***	-0.110***	-0.170***	-0.0347	-0.120***	-0.107***
	(0.0317)	(0.0315)	(0.0399)	(0.0278)	(0.0388)	(0.0389)
travelden		0.0365***		0.219***		0.0216***
		(0.00560)		(0.00494)		(0.00692)
temper	0.0260***	0.0250***	0.0360***	0.0297***	0.0188***	0.0182***
	(0.00263)	(0.00260)	(0.00331)	(0.00229)	(0.00322)	(0.00321)
humidity	0.0141***	0.0141***	0.00399***	0.00427***	-0.00605***	-0.00602***
	(0.000480)	(0.000475)	(0.000604)	(0.000418)	(0.000588)	(0.000586)
wind	-0.194***	-0.185***	-0.361***	-0.309***	-0.285***	-0.280***
	(0.0167)	(0.0166)	(0.0210)	(0.0146)	(0.0204)	(0.0205)
Constant	-0.259***	-0.427***	3.909***	2.903***	3.634***	3.535***
	(0.0479)	(0.0539)	(0.0603)	(0.0475)	(0.0586)	(0.0665)
city fixed	Y	Y	Y	Y	Y	Y
time trend	Y	Y	Y	Y	Y	Y
Observations	1848	1848	1848	1848	1848	1848
R-squared	0.579	0.589	0.318	0.673	0.309	0.313
Number of id	28	28	28	28	28	28

Panel A and B address the mediating effect of the intracity migration index on the relationship between the lockdown and AQI, $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2. Column (1) shows the impact of the lockdown on the, which shows that, compared with non-locked-down cities, the lockdown reduced the intracity migration index of the locked-down cities in the “2+26” cities by 0.617 on average. Therefore, the lockdown reduced the intracity migration index. Column (2) shows the results of the basic regression, i.e., the impact of the lockdown on the AQI. The result shows that the lockdown reduced the AQI of the locked-down cities by 16.7% on average. Column (3) shows the impact of the lockdown on the AQI after controlling the mediating variable. The results show that the coefficient was positive at the 1% level, indicating that the mediating effect was significant. The results in columns (4)-(13) also provide similar evidence. Furthermore, our calculations found that the lockdown reduced AQI, $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2 by 3.54, 3.05, 6.48, 2.25, 13.51 and 1.33% on average, respectively, by reducing the intracity migration index. Therefore, the lockdown reduced air pollution by reducing the intracity migration index.

Table 7. Mediating Effect Test: The Urban Immigration Scale Index

Panel C	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	immigrate	lnAQI	lnAQI	lnPM$_{2.5}$	lnPM$_{2.5}$	lnPM$_{10}$	lnPM$_{10}$
lockdown	-1.121***	-0.167***	-0.0920**	-0.271***	-0.196***	-0.279***	-0.134***
	(0.0713)	(0.0361)	(0.0381)	(0.0447)	(0.0474)	(0.0426)	(0.0443)
immigrate			0.0665***		0.0670***		0.129***
			(0.0118)		(0.0146)		(0.0137)
temper	0.00561	0.0360***	0.0356***	0.0503***	0.0499***	0.0548***	0.0541***
	(0.00591)	(0.00299)	(0.00297)	(0.00370)	(0.00369)	(0.00353)	(0.00345)
humidity	-0.000855	0.0158***	0.0159***	0.0250***	0.0251***	0.0153***	0.0154***
	(0.00108)	(0.000546)	(0.000542)	(0.000677)	(0.000673)	(0.000645)	(0.000630)
wind	-0.0568	-0.175***	-0.171***	-0.277***	-0.273***	-0.201***	-0.194***
	(0.0376)	(0.0190)	(0.0189)	(0.0236)	(0.0234)	(0.0224)	(0.0219)
Constant	1.885***	4.135***	4.009***	3.332***	3.206***	4.142***	3.899***
	(0.108)	(0.0545)	(0.0584)	(0.0675)	(0.0726)	(0.0643)	(0.0679)
city fixed	Y	Y	Y	Y	Y	Y	Y
time trend	Y	Y	Y	Y	Y	Y	Y
Observations	1848	1848	1848	1848	1848	1846	1846
R-squared	0.342	0.531	0.539	0.612	0.616	0.437	0.463
Number of id	28	28	28	28	28	28	28

Panel D	(8)	(9)	(10)	(11)	(12)	(13)
VARIABLES	lnCO	lnCO	lnNO$_2$	lnNO$_2$	lnSO$_2$	lnSO$_2$
lockdown	-0.132***	-0.0745**	-0.170***	0.124***	-0.120***	-0.0903**
	(0.0317)	(0.0336)	(0.0399)	(0.0376)	(0.0388)	(0.0413)
travelden		0.0516***		0.263***		0.0265**
		(0.0104)		(0.0116)		(0.0128)
temper	0.0260***	0.0257***	0.0360***	0.0345***	0.0188***	0.0187***
	(0.00263)	(0.00261)	(0.00331)	(0.00292)	(0.00322)	(0.00321)
humidity	0.0141***	0.0141***	0.00399***	0.00421***	-0.00605***	-0.00602***
	(0.000480)	(0.000477)	(0.000604)	(0.000534)	(0.000588)	(0.000587)
wind	-0.194***	-0.191***	-0.361***	-0.346***	-0.285***	-0.284***
	(0.0167)	(0.0166)	(0.0210)	(0.0186)	(0.0204)	(0.0204)
Constant	-0.259***	-0.357***	3.909***	3.414***	3.634***	3.584***
	(0.0479)	(0.0515)	(0.0603)	(0.0576)	(0.0586)	(0.0633)
city fixed	Y	Y	Y	Y	Y	Y
time trend	Y	Y	Y	Y	Y	Y

Observations	1848	1848	1848	1848	1848	1848
R-squared	0.579	0.585	0.318	0.468	0.309	0.311
Number of id	28	28	28	28	28	28

Panel C and D show the mediating effect of the urban immigration scale index on the relationship between the lockdown and AQI, $PM_{2.5}$, PM_{10}, CO, NO_2 and SO_2. Furthermore, our calculations showed that the lockdown decreased AQI, $PM_{2.5}$, PM_{10}, CO, and SO_2 by 7.45, 7.51, 14.46, 5.78 and 2.97% on average, respectively, via urban immigration scale index. Therefore, the lockdown cut down air pollution by reducing the urban immigration scale index, and thus, the hypothesis H2 was verified.

4. Robustness Checks

To test the robustness of the empirical results, we selected different samples to further verify whether the relationship between the lockdown and air pollution and its micro-mechanisms was consistent with those in the "2+26" cities. Therefore, another heavily polluted area, the Yangtze River Delta region in China, was chosen for a robustness test. Based on the panel data of 27 cities in the central area of the Yangtze River Delta region from 10 January to 15 March 2020, we took 10 locked-down cities in this region as the treatment group, and the other 17 non-locked-down cities as the control group, and established a parallel trend test model, a multi-phase DID model and a mediating effect test model to conduct research. The empirical results and analysis are shown below.

4.1 Parallel Trend Test

We took $\ln AQI$, $\ln PM_{2.5}$, $\ln PM_{10}$, $\ln CO$, $\ln NO_2$ and $\ln SO_2$ as the dependent variables to regress model (2).

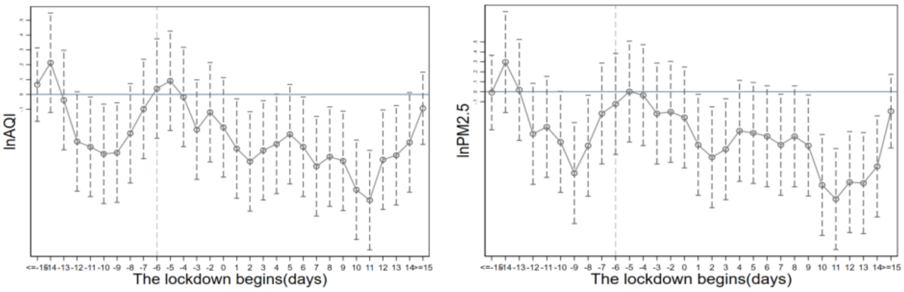

Figure 6. Dynamic Effects of the Lockdown on $\ln AQI$ and $\ln PM_{2.5}$

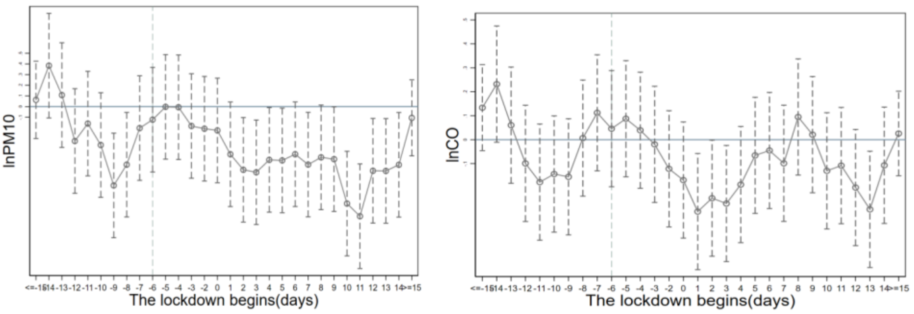

Figure 7. Dynamic Effects of the Lockdown on lnPM$_{10}$ and lnCO

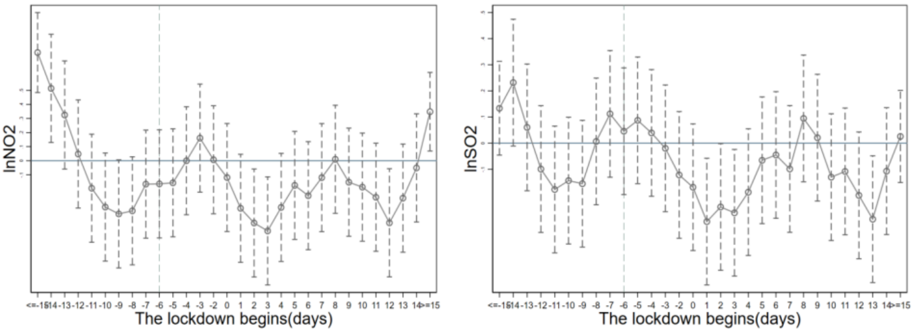

Figure 8. Dynamic Effects of the Lockdown on lnNO$_2$ and lnSO$_2$

Figures 6-8 show that the coefficient β_1 mainly fluctuated around 0 before the lockdown, which means that the treatment and control groups had the same trend of air pollution. The results are consistent with the parallel trend test in the “2+26” cities; therefore, the results of the parallel trend test are robust.

4.2 Multi-Phase DID

Similar to the previous analysis, we used the panel data of 27 cities in the central area of the Yangtze River Delta region from 10 January to 15 March to regress model (3). The results of the regression are shown in Table 7.

Table 8. Multi-Phase DID for the Yangtze River Delta Region

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	lnAQI	lnPM$_{25}$	lnPM$_{10}$	lnCO	lnNO$_2$	lnSO$_2$
lockdown	-0.189***	-0.258***	-0.234***	-0.111***	-0.236***	-0.0151
	(0.0332)	(0.0500)	(0.0467)	(0.0249)	(0.0402)	(0.0224)
temper	0.0158***	0.0425***	0.0486***	0.0197***	0.0459***	0.0114***
	(0.00363)	(0.00546)	(0.00510)	(0.00273)	(0.00440)	(0.00245)
humidity	-0.0106***	-0.0134***	-0.0184***	-0.000415	-0.00210***	-0.0101***

	(0.000670)	(0.00101)	(0.000942)	(0.000503)	(0.000812)	(0.000452)
wind	-0.194***	-0.337***	-0.271***	-0.144***	-0.384***	-0.110***
	(0.0172)	(0.0259)	(0.0242)	(0.0129)	(0.0208)	(0.0116)
Constant	5.421***	5.328***	5.704***	0.000928	3.751***	2.808***
	(0.0658)	(0.0990)	(0.0925)	(0.0494)	(0.0797)	(0.0444)
city fixed	Y	Y	Y	Y	Y	Y
time trend	Y	Y	Y	Y	Y	Y
Observations	1782	1782	1782	1782	1782	1782
R-squared	0.252	0.245	0.258	0.212	0.233	0.256
Number of id	27	27	27	27	27	27

Columns (1)-(6) show the results of the impact of the lockdown on air pollution. The results show that compared with non-locked-down cities, the lockdown reduced the air pollution in locked-down cities of the Yangtze River Delta region. Hence, the result of the basic regression with the "2+26" cities was robust, and hypothesis H_1 was verified.

4.3 Mediating Effect Test

We used the panel data of 27 cities in the central area of the Yangtze River Delta region from 10 January to 15 March to regress models (4)-(6) (for simplicity, the results are not presented here, see Appendix for details). A mediating effect existed and the lockdown reduced air pollution by reducing the intracity migration index and the urban immigration scale index. Therefore, the results of the mediating effect test were robust and hypothesis H_2 was verified.

5. Further Analysis

The previous analyses showed that, compared with the non-locked-down cities, the lockdown significantly reduced air pollution in the "2+26" cities. We then tested whether the lockdown reduced the air pollution in the "2+26" cities compared with the same period in the lunar calendar in 2019. If the lockdown also reduced air pollution in the locked-down cities compared with the same period of the lunar calendar in 2019, we can infer that the lockdown improved air quality greatly compared with cities during the times of normal human activity without the COVID-19 lockdown. This would provide further proof of the close connection between air pollution and human activities.

Therefore, based on the panel data of eight cities of the "2+26" cities from 10 January to 15 March and the same period of the lunar calendar in 2019, we used the multi-period DID model and the mediating effect model to verify whether the lockdown reduced air pollution in locked-down cities and to explore the micro-mechanisms of reduced air pollution.

5.1 Multi-Phase DID Model

A multi-phase DID model was established as follows.

$$\ln Y_{it} = \beta_0 + \beta_1 time_t * treat_t + \beta_2 X + \alpha_i + \lambda_t + \varepsilon_{it} \tag{7}$$

where $\ln Y_{it}$ represents the air pollution of city i during period t, and $time_t * treat_i$ is the interaction term of $time$ and $treat$; $time_t * treat_i$ equaled 1 for the period after the lockdown in 2020 and equaled 0 for the same period of the lunar calendar in 2019. β_1 is the impact of the lockdown on air pollution compared with the same period in the lunar calendar in 2019. Other variables are the same as defined in model (2).

We regress model (6), where the results of the regression are shown in Table 9.

Table 9. Multi-Period DID Results

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	lnAQI	$\ln PM_{25}$	$\ln PM_{10}$	lnCO	$\ln NO_2$	$\ln SO_2$
lockdown	-0.254^{***}	-0.172^{***}	-0.196^{***}	-0.0107	-0.315^{***}	-0.0563
	(0.0385)	(0.0516)	(0.0450)	(0.0396)	(0.0382)	(0.0435)
Constant	4.156^{***}	3.522^{***}	4.325^{***}	-0.0425	4.632^{***}	3.403^{***}
	(0.0932)	(0.125)	(0.109)	(0.0959)	(0.0924)	(0.105)
Control variables	Y	Y	Y	Y	Y	Y
city fixed	Y	Y	Y	Y	Y	Y
time trend	Y	Y	Y	Y	Y	Y
Observations	1055	1055	1055	1055	1055	1055
R-squared	0.687	0.729	0.643	0.644	0.677	0.485
Number of id	16	16	16	16	16	16

The results show that, compared with the same period of the lunar calendar in 2019, the lockdown reduced AQI, $PM_{2.5}$, PM_{10}, and NO_2 of the locked-down cities of the "2+26" cities by 25.4, 17.2, 19.6 and 31.5% on average, respectively. Thus, we could infer that the lockdown reduced the air pollution of the locked-down cities.

5.2 Mediating Effect Test Model

We tested whether the lockdown reduced air pollution of the locked-down cities in the "2+26" cities compared with the same period in the lunar calendar in 2019 by reducing the intracity migration index and the urban immigration scale index. The results of the regressions of the lockdown against CO and

SO_2 were not significant. The mediating effect test results for AQI, $PM_{2.5}$, PM_{10}, and CO are shown in Tables 10 and 11.

Table 10. Mediating Effect Test: The Intracity Migration Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	travelden	lnAQI	lnAQI	ln$PM_{2.5}$	ln$PM_{2.5}$	lnPM_{10}	lnPM_{10}	lnNO_2	lnNO_2
time* treat	-1.702***	-0.254***	-0.169***	-0.172***	-0.0931	-0.196***	-0.100*	-0.315***	-0.115***
	(0.0858)	(0.0385)	(0.0454)	(0.0516)	(0.0610)	(0.0450)	(0.0530)	(0.0382)	(0.0437)
travelden			0.0500***		0.0466**		0.0563***		0.117***
			(0.0143)		(0.0193)		(0.0167)		(0.0138)
Constant	5.918***	4.156***	3.860***	3.522***	3.246***	4.325***	3.992***	4.632***	3.937***
	(0.208)	(0.0932)	(0.126)	(0.125)	(0.169)	(0.109)	(0.147)	(0.0924)	(0.121)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y
city fixed	Y	Y	Y	Y	Y	Y	Y	Y	Y
time trend	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1055	1055	1055	1055	1055	1055	1055	1055	1055
R-squared	0.687	0.687	0.690	0.729	0.730	0.643	0.647	0.677	0.700
Number of id	16	16	16	16	16	16	16	16	16

Table 10 shows the mediating effect of the intracity migration index on the impact of the lockdown on AQI, $PM_{2.5}$, PM_{10}, and NO_2. Our calculations showed that, compared with the same period of the lunar calendar in 2019, the lockdown reduced AQI, $PM_{2.5}$, PM_{10}, and NO_2 by 8.51, 7.93, 9.58 and 19.91% on average, respectively, by reducing the intracity migration index. Hence, we could infer that the lockdown reduced air pollution by reducing the intracity migration index.

Table 11. Mediating Effect Test: The Urban Immigration Scale Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	immigrate	lnAQI	lnAQI	ln$PM_{2.5}$	ln$PM_{2.5}$	lnPM_{10}	lnPM_{10}	lnNO_2	lnNO_2
time* treat	-1.745***	-0.254***	-0.256***	-0.172***	-0.150***	-0.196***	-0.209***	-0.315***	-0.266***
	(0.176)	(0.0385)	(0.0404)	(0.0516)	(0.0541)	(0.0450)	(0.0472)	(0.0382)	(0.0397)
immigrate			-0.00111		0.0131		-0.00741		0.0284***
			(0.00704)		(0.00942)		(0.00822)		(0.00692)
Constant	4.384***	4.156***	4.161***	3.522***	3.464***	4.325***	4.358***	4.632***	4.507***

	(0.425)	(0.0932)	(0.0983)	(0.125)	(0.131)	(0.109)	(0.115)	(0.0924)	(0.0966)
Control variables	Y	Y	Y	Y	Y	Y	Y	Y	Y
city fixed	Y	Y	Y	Y	Y	Y	Y	Y	Y
time trend	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	1055	1055	1055	1055	1055	1055	1055	1055	1055
R-squared	0.282	0.687	0.687	0.729	0.729	0.643	0.643	0.677	0.683
Number of id	16	16	16	16	16	16	16	16	16

Through the mediating effect test and the Sobel test, it was calculated that compared with the same period in the lunar calendar in 2019, the lockdown reduced $PM_{2.5}$ and NO_2 by an average of 2.29 and 4.96%, respectively, through reducing the urban immigration scale index. The mediating effect of the urban immigration scale index on AQI and PM_{10} was not significant.

Overall, compared with the same period in the lunar calendar in 2019, the lockdown mainly reduced air pollution of the locked-down cities in the “2+26” cities by reducing the intracity migration index. Furthermore, we conducted a comparison of two multi-phase DID models, one of which took non-locked-cities as the control group, and the other took locked-down cities in the same period of the lunar calendar in 2019 as the control group. We found that the mediating effect of the intracity migration index was stronger when taking the same period of the lunar calendar in 2019 as the control group. In fact, under the influence of the COVID-19 pandemic, the non-locked-down cities also implemented epidemic prevention measures, and the intracity migration was reduced greatly, whereas the cities in the same period of the lunar calendar in 2019 were not affected by the COVID-19 pandemic, and the intracity migration index was at a normal level. Therefore, compared with the same period of the lunar calendar in 2019, the mediating effect of intracity migration was stronger, which further showed that the air pollution was mainly caused by human activities.

6. Conclusions and Recommendations

In December 2019, a novel coronavirus began to break out in Wuhan, China, and then spread across the country. Facing a severe epidemic, after 23 January 2020, cities across China successively adopted severe lockdown measures. The lockdown reduced human mobility, thereby reducing industrial production and traffic. Based on the data of 28 cities in the “2+26” cities from 10 January to 15 Marc, this study used a parallel trend model, a multi-phase DID model and a mediating effect test model to investigate whether the lockdown reduced air pollution by reducing human mobility. Furthermore, we use the data of 27 cities in the central area of the Yangtze River Delta region to verify the robustness of the empirical results. We also took the locked-down cities in the same period of the lunar calendar in 2019 as the control group to investigate whether the lockdown reduced air pollution by reducing human mobility compared with the same period in 2019. The research conclusions are as follows.

First, the lockdown against the COVID-19 pandemic significantly reduced air pollution. Compared with non-locked-down cities, the lockdown reduced the AQI, $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2 of the locked down cities by an average of 16.7, 27.1, 27.9, 13.2, 17.0 and 12.0%, respectively. The air quality improved.

Second, the lockdown reduced air pollution by reducing the intracity migration index and the urban immigration scale index. The lockdown reduced AQI, $PM_{2.5}$, PM_{10}, CO, NO_2, and SO_2 by an average of 3.54, 3.05, 6.48, 2.25, 13.51 and 1.33%, respectively, through reducing the Intracity migration index, the lockdown also reduces AQI, $PM_{2.5}$, PM_{10}, CO, and SO_2 by an average of 7.45%, 7.51%, 14.46%, 5.78%, and 2.97% through reducing the urban immigration scale index. Therefore, urban air quality was improved by reducing the intracity migration index and the urban immigration scale index.

Third, compared with the same period in the 2019 lunar calendar, the lockdown reduced AQI, $PM_{2.5}$, PM_{10}, and NO_2 in the locked-down cities by an average of 25.4, 17.2, 19.6 and 31.5%, respectively, through reducing the intracity migration index, and reduced AQI, $PM_{2.5}$, PM_{10}, and NO_2 by an average of 8.51, 7.93, 9.58 and 19.91%, respectively, through the urban immigration scale index. The lockdown reduced $PM_{2.5}$ and NO_2 by an average of 2.29 and 4.96%, respectively.

Although the lockdown restricted the human mobility and industrial production, and hence caused economic and social losses to a large extent, this study found that the lockdown reduced air pollution and improved air quality. We also found that the lockdown impacted air pollution through the intracity migration index and the urban immigration scale index, which are mainly induced by industrial production and human mobility.

Based the above conclusions, we propose relevant policy recommendations.

We should encourage citizens to travel in a green way, using public transport, bicycles and walking. The intracity migration index and the urban immigration scale index are important factors affecting air pollution, and human mobility is mainly associated with industrial production and transportation.

Enterprises should adopt green production technology to reduce the impact on the environment. The halt of industrial production and traffic caused by the lockdown reduced air pollution, and since work has been resumed and production has been resumed in turn, air pollution will return to or even exceed the previous level. Green technological innovations are the fundamental factors for reducing air pollution for enterprises.

Various measures and policies should be enacted to stimulate the endogenous power of green development of enterprises. The key to reducing air pollution lies in green production. However, the excessively high cost of enterprise innovation may inhibit technological innovations. Governments could offer some necessary subsidies for enterprises to promote technological innovations.

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