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Heterogeneous effects of COVID-19 lockdown measures on air quality in Northern China

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ABSTRACT

In response to the spread of COVID-19, China implemented a series of control measures. The causal effect of these control measures on air quality is an important consideration for extreme air pollution control in China. Here, we established a difference-in-differences model to quantitatively estimate the lockdown effect on air quality in the Beijing-Tianjin-Hebei (BTH) region. We found that the lockdown measures did have an obvious effect on air quality. The air quality index (AQI) was reduced by 15.2%, the concentration of NO2, PM10, PM2.5, and CO were reduced by 37.8%, 33.6%, 21.5%, and 20.4% respectively. At the same time, we further explored the heterogeneous effects of travel restrictions and the control measure intensity on air quality. We found that the traffic restrictions, especially the restriction of intra-city travel intensity (TI), exhibited a significant heterogeneous effect on NO2 with a decrease of approximately 13.6%, and every one-unit increase in control measures intensity reduced the concentration of air pollutants by approximately 2–4%. This study not only provides a natural, experimental basis for control measures on air quality but also indicates an important direction for future control strategies. Importantly, determining the estimated effect helps formulate accurate and effective intervention measures on the differentiated level of air pollution, especially on extreme air pollution.

1. Introduction

Coronavirus disease 2019 (COVID-19) spread internationally and triggered a global public health crisis [1]. In China, it was initially identified in Wuhan in December 2019, then quickly spread around China and became a global infectious disease [2]. China has taken a series of control measures to prevent upgrades in the epidemic spread [3]. The Chinese government implemented full lockdown for the serious epidemic in Wuhan, carried out comprehensive prevention and control measures according to the risk level in other regions, closed public places, strengthened the prevention and control of public service facilities, cancelled or delayed all kinds of public gatherings, and implemented telecommuting and teaching.1

There is no doubt that there was a huge economic cost of implementing these restrictions [4,5]. On the one hand, the epidemic has spread rapidly around the world, directly harmful to the capital markets. On the other hand, to control the spread of the epidemic, countries have taken measures such as controlling production activities, which will also harm social and economic operation [6]. In addition, the epidemic is also damaging energy supplies in the energy sector, such as the electricity sector [7].

Nevertheless, there have been unintended environmental benefits, resulting in a drop in carbon emissions and air pollutant concentrations, especially NO2, during the Spring Festival [8,9]. Reduced economic activity and traffic restrictions have led directly to changes in China’s energy consumption, thereby preventing environmental pollution [10]. Pollution levels in China dropped sharply in a matter of days because of the restrictions on human activities and traffic [11]. The reduction in NO2 pollution was first apparent in Wuhan and then spread across the rest of the country, and NO2 emissions were reduced by approximately

1 The Report on China’s practices in combating COVID-19 was conducted by the Chinese observer think tank, China Daily, in collaboration with the National Conditions Research Institute of Tsinghua University and the School of Health Management and Policy at Peking Union Medical College, after consulting more than 60 public health experts and Chinese and foreign scholars. http://cn.chinadaily.com.cn/a/202004/21/WS5e9e4e66a310c00b7c785ed.html.
30% during the COVID-19 outbreak (NASA, 2020). The concentration of major pollutants on the ground also dropped significantly in most parts of China [1,12].

A range of air pollution concentration monitoring data provided evidence of declining air pollution during the COVID-19 outbreak, but the evidence was insufficient to show how and to what extent lockdown measures affected air quality during the COVID-19 outbreak. Chauhan and Singh [13] found that PM2.5 in big cities such as Beijing and Shanghai decreased by approximately 50% by comparing the PM2.5 data of ground stations during 2019–2020 with that of the past three years, wherein the decrease of PM2.5 for different months was related to the implementation of urban lockdowns. Mahato et al. [14] compared air pollutant concentrations before and during the lockdown in Delhi (India) and found the average concentration of PM10 and PM2.5 decreased by 60% and 39%, respectively, followed by decreases in the NO2 and CO levels of 52.68% and 30.35%, respectively. Tobias et al. [15] assessed the change in average air pollutant concentrations before and during the control measures in Barcelona (Spain) and found that the most significant reductions were 45% and 51% for black carbon (BC) and PM10, respectively, which was mainly related to the reduction in traffic emissions.

Several studies have been carried out on the control measure mechanisms for air quality during the COVID-19 outbreak. Most of the studies were carried out by simulating the correlation between different control measures and air quality. Wang et al. [12] simulated three different emissions cases during the control period using the Community Multiscale Air Quality (CMAQ) model and found that the reduction of anthropogenic emissions, mainly traffic and industrial emissions, contributed to the reduction in PM2.5 concentrations by 10–20%. Li et al. [16] studied the correlation between human and industrial activities and air pollution in the Yangtze River Delta region of China through photochemical modelling and found that the concentrations of PM2.5, NO2, and SO2 decreased by 31.8%, 45.1%, and 20.4% year-on-year during the lockdown level I response, respectively. The level II response period saw reductions of 33.2%, 27.2%, and 7.6%, respectively.

Several empirical studies have been carried out on the effect of lockdown control measures on air quality. Bao and Zhang [17] used the Least Square Dummy Variable (LSDV) model to study the changes in air pollutant concentrations in 44 cities across northern China. The air quality index (AQI) decreased by 7.80% on average, and the concentrations of the five air pollutants (SO2, PM2.5, PM10, NO2, CO) decreased by 6.76%, 5.93%, 14.82%, 24.47%, and 4.58%, respectively. Since the COVID-19 lockdown was an external intervention, its effect can be more quantitatively identified by using quasi-experimental methods. He et al. [18] used two groups of difference in differences (DiD) models to quantify the effect of control measures. Compared with non-controlled cities, weekly AQI and PM2.5 in controlled cities decreased by 19.4 points (18%) and 13.9 g/m³ (17%), respectively. Meanwhile, compared with the same period in 2019, the AQI dropped by 8.8 points (7%) and PM2.5 fell by 8.4 points (8%).

The Beijing-Tianjin-Hebei (BTH) region is one of the major economic zones in northern China. Air pollution in this region has always been a huge concern, especially in winter [19]. When meteorological conditions are unfavourable, air pollution usually becomes more serious than in other areas due to the unique topography [20]. Since the implementation of the control policy on 23 January 2020, almost all industries except power plants and large-scale enterprises were closed, and traffic was also restricted. This should have resulted in a significant improvement in air quality. However, regional heavy air pollution was still present after the implementation of extreme control measures [12]. The objectives of this study are to (i) explore the causal effect of COVID-19 lockdown measures; (ii) quantitatively estimate the heterogeneous improvements in air pollutant concentrations due to comprehensive lockdown measures; (iii) identify classified control strategies for facing differentiated levels of air pollutants and extreme air pollution.

Our study chose data including daily air pollutant concentrations and weather conditions in the BTH region and designed a DiD model to quantitatively identify the effect of control measures on air pollution during the COVID-19 outbreak. In addition, we innovatively studied the causal relationship between traffic restrictions and the intensity of control measures on air pollutants. Specifically, we used the population migration index from Baidu Maps to estimate the effect of travel restrictions on air pollution reduction. Moreover, we used the implementation stringency index of control measures collected by the Oxford COVID-19 Government Response Tracker (OxCGRT) to explore the relationship between control intensity and air pollution reduction.

The remainder of this paper is structured as follows. Section 2 introduces the empirical strategy. Section 3 reveals the effects of control measures on air pollution during the COVID-19 outbreak. Section 4 examines the heterogeneity of the effects, the role of travel restrictions, and the intensity of the measures. Section 5 presents the discussion on the implications of measures for air pollution control and Section 6 concludes this study.

2. Data and methods

2.1. Empirical methods

First, we used LSDV estimation strategies to observe the effect of the Spring Festival and the COVID-19 control measures on air quality. Our main model is a city fixed effect panel data model, as follows:

$$\ln P_{it} = \alpha_0 + \alpha_1 \text{Corona} + \alpha_2 \text{Holiday} + \alpha_3 \text{Other holidays} + \theta_1 W_{it} + \theta_2 X_{it} + \mu_i + \pi_t + \epsilon_{it}$$

where \(\ln P_{it}\) is the dependent variable and is the logarithm of the daily mean air pollutant concentration (AQI, PM2.5, PM10, NO2, CO) in city i on day t; “Corona” was set as 1 if it was a day during the initial COVID-19 outbreak (2020.1.24–2020.2.29). “Holiday” is the dummy variable that took the value 1 if it is in the Spring Festival (2019.2.4–2019.2.10 or 2020.1.24–2020.2.2). “Other holidays” is a dummy variable for holidays other than the Spring Festival. \(W_{it}\) describes the daily weather variables (daily mean temperature, daily mean relative humidity, daily mean wind speed, and daily mean accumulated precipitation over 12 h) in city i on day t. \(X_{it}\) describes other vector control variables, including the influence of Year and Month. \(\mu_i\) indicates city fixed effects, \(\pi_t\) indicates date fixed effects, and \(\epsilon_{it}\) is the error term.

DiD models have been widely used to evaluate the causal effect of government regulations on the atmospheric and separate policy influences from other influencing factors [21]. These models can eliminate uncontrollable and unpredictable factors in the periods before and after the regulation implementation [22].

As the COVID-19 controls coincided with China’s Spring Festival, which changed people’s production and consumption activities and affected air pollution, it is necessary to separate the Spring Festival holiday effect [23]. We chose the air pollution data in 2020 as the experimental group and the same period in 2019 as the control group. Since the Spring Festival in 2020 was extended to 2 February 2020, we sourced data 10 days before and after the start of the Spring Festival in 2020 (2020.1.14–2020.2.2) and the same period in 2019 (2019.1.25–2019.2.13). The DiD model is as follows:

$$\ln P_{it} = \beta_0 + \beta_1 \text{Holiday} \times \text{Treat} + \beta_2 \text{Holiday} + \beta_3 \text{Treat} + \theta_4 X_{it} + \mu_i + \pi_t + \epsilon_{it}$$

where “Treat” is a grouping dummy variable. It was set as 1 if it is in the year 2020, and 0 for 2019. Holiday was set as 1 if it is after the Spring Festival.
Festival (2019.2.4 or 2020.1.24) in our study period. The interaction term Holiday \times Treat represents the COVID-19 control measures during the Spring Festival Holiday in 2020.

Here, heterogeneous effects of travel restrictions and the control measure intensity on air quality were explored in our study.

\[ \ln P_i = \gamma_0 + \gamma_1 \text{TI} + \gamma_2 \text{MI} + \gamma_3 \text{MO} + \gamma_4 \text{Corona} + \gamma_5 \text{Holiday} + \theta_1 W_a + \theta_2 X_t + \mu_i + \epsilon_i \]  

(3)

Restrictions in the BTH region during COVID-19 reduced air pollutant concentrations, but the relationship between specific measures and pollutant concentrations has received little attention. OxCGRT collected information on several different common policy responses by governments to the COVID-19 pandemic.\(^3\) We chose policy indicators including school closures, workplace closures, cancelled public events, restrictions on gatherings, public transport closures, stay at home requirements, restrictions on internal movement, and international travel controls. The indicators Control were combined to reflect the overall intensity of COVID-19 control measures, and replaced COVID-19 control in the explanatory model to quantitatively reflect the intensity’s influence on air pollutant concentrations:

\[ \ln P_i = \rho_0 + \rho_1 \text{Control} + \rho_2 \text{Holiday} + \theta_1 W_a + \theta_2 X_t + \mu_i + \epsilon_i \]  

(4)

To choose the valid model, we employed the Hausman test and confirmed the correct use of fixed effects in these panels (Eqs. (1), (3) and (4)). The dependent variables in all the four equations are logarithmic processed in order to avoid possible heteroscedasticity and reduce data fluctuations. And the relative changes can be interpreted more easily.\(^{26,27}\)

2.2. Data

Air quality data was taken from the National Urban Air Quality real-time release platform of China’s Environmental Monitoring Station. The data set included hourly readings of the AQL, PM2.5, PM10, SO\(_2\), NO\(_2\), and CO from 1605 air quality monitoring stations, covering all of China’s prefecture-level cities. We folded the data set into prefecture-level cities according to the site locations and collected daily pollutant concentration data (AQL, PM2.5, PM10, SO\(_2\), NO\(_2\), CO) from 13 cities from 2019.1.1 to 2020.2.29 in the BTH region.

Meteorological data was sourced from China’s daily surface meteorological data provided by the National Meteorological Information Center, which collects meteorological records from surface meteorological stations.\(^4\) We used the same method as for the air quality data to collapse the site data into city-level datasets. Daily meteorological data (daily mean temperature, daily mean relative humidity, daily mean wind speed, and daily precipitation (accumulated over 24 h)) for 13 cities in the BTH region were collected.

We matched the meteorological data and air quality data based on the geographical coordinates of the stations and prefecture-level cities, following the procedures employed in a previous study by Fan et al.\(^{28}\). For prefecture-level cities with urban monitoring stations, we used the averaged data from air quality monitoring stations located in the same city, while for cities without monitoring stations, we matched the stations within a radius of 100 km to the geometric centre of each city and calculated their daily means. Table 1 presents the summary statistics of our key variables.

3. Empirical results

3.1. Changes in air quality during the Spring Festival

We start by presenting changes in air quality in the BTH region during the Spring Festival in 2019 and 2020 (Fig. 1). The air quality levels before the Spring Festival in 2019 and 2020 were approximately equal, indicating that the parallel trend assumption may hold. With the implementation of COVID-19 control measures in 2020, the concentration of NO\(_2\) in the 2020 Spring Festival was significantly lower than that in 2019, with little difference in the concentration of other pollutants. AQL, PM2.5, PM10, and SO\(_2\) were lower over approximately 10 days than in 2019, and the CO values overlapped with the 2019 results. This result indicated that the air quality of the control city slightly improved, although a delay effect could have occurred. However, it is worth noting that during the Spring Festival, the concentration of pollutants in 2020 was higher than that in 2019, rising first and then falling, which may have been due to the influence of adverse meteorological factors in 2020. Compared with the previous Spring Festival periods, the BTH region in 2020 experienced higher relative humidity and temperature, which facilitated multiphase reactions for aerosol formation and growth. Low wind and little precipitation were also favorable for haze formation.\(^{12,29}\) These meteorological conditions may obscure the true impact of the COVID-19 control measures. So to better understand the effect of COVID-19 control measures as opposed to exceptional weather conditions, meteorological variables were controlled in the model.

3.2. Effects of control measures on air quality

First, we carried out a regression using the model in Eq. (1) on the factors affecting air pollutant concentrations from 2019.1.1 to

\[ \begin{align*}
\text{Table 1} & \quad \text{Summary statistics of key model variables.} \\
\text{Variables} & \quad \text{Unit} & \quad \text{Obs.} & \quad \text{Mean} & \quad \text{Std. Dev.} & \quad \text{Min} & \quad \text{Max} \\
\text{AQL} & \quad \text{N/A} & \quad 5507 & \quad 86.223 & \quad 52.148 & \quad 14.750 & \quad 430.083 \\
\text{PM2.5} & \quad \mu g/m^3 & \quad 5507 & \quad 53.787 & \quad 46.000 & \quad 3.667 & \quad 400.250 \\
\text{PM10} & \quad \mu g/m^3 & \quad 5507 & \quad 93.230 & \quad 62.205 & \quad 7.957 & \quad 508.250 \\
\text{SO}_2 & \quad \mu g/m^3 & \quad 5507 & \quad 14.302 & \quad 9.666 & \quad 1.458 & \quad 78.292 \\
\text{NO}_2 & \quad \mu g/m^3 & \quad 5507 & \quad 38.106 & \quad 19.157 & \quad 3.250 & \quad 117.875 \\
\text{CO} & \quad \text{mg/m}^3 & \quad 5507 & \quad 1.006 & \quad 0.635 & \quad 0.144 & \quad 7.417 \\
\text{Temperature} & \quad ^\circ \text{C} & \quad 5507 & \quad 11.217 & \quad 11.721 & \quad -14.233 & \quad 33.6 \\
\text{Humidity} & \quad \% & \quad 5507 & \quad 56.625 & \quad 19.185 & \quad 11.000 & \quad 100 \\
\text{Wind speed} & \quad \text{m/s} & \quad 5507 & \quad 2.158 & \quad 1.033 & \quad 0.300 & \quad 7.500 \\
\text{Precipitation} & \quad \text{mm} & \quad 5507 & \quad 1.040 & \quad 4.586 & \quad 0 & \quad 84.333
\end{align*} \]

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\(^3\) OxCGRT collected 17 indices regarding the government’s response including 8 stem and closed policy indicators, such as school closures and travel restrictions, 4 indicators on economic policy, such as income support for citizens or foreign aid, and 5 measures on health systems policy, such as COVID-19 or emergency health care investment and detection systems.

\(^4\) The National Meteorological Information Center provided the daily data for the pressure, temperature, precipitation, evaporation, relative humidity, wind direction and speed, sunshine duration, and ground temperature at 699 surface meteorological stations across China since January 1951.
We found that the implementation of control measures significantly reduced air pollutant concentrations indicating that they improved air quality. The AQI decreased by 10.1%, NO\textsubscript{2} decreased by 51.1%, followed by PM\textsubscript{2.5}, SO\textsubscript{2}, PM\textsubscript{10}, and CO, which decreased by 28.8%, 23.9%, 18.7%, and 15.1%, respectively. The Spring Festival and other holidays had little or no significant effect on air pollutant concentrations except the NO\textsubscript{2} and CO. However, the meteorological factors showed strong explanatory power. The time variables (Year and Month) represent the long-term time trend due to the annual or the monthly variation of air pollutants \cite{30}, also exhibited a significant effect on air pollutant concentrations. The constants are all statistically significant, indicating that it well balanced the error terms not accounted for by other terms in the model, and guarantees that the residuals have a mean of zero.

We used the DID model (Eq. (2)) to separate control measures during the COVID-19 outbreak from the Spring Festival effect and quantitatively identify the net effect of control measures on air quality. We set the air pollutant concentrations in 2019 as a control group (where no control measures were implemented), and the air pollutant concentrations in 2020 as the experimental group. The results of the DID analyses (Table 3) demonstrated that the control measures improved the air quality compared with the same period in 2019. The AQI decreased by 15.2%, NO\textsubscript{2} decreased by 37.8%, followed by PM\textsubscript{10}, PM\textsubscript{2.5}, and CO, which decreased by 33.6%, 21.5%, and 20.4%, respectively. However, there was no significant effect observed for SO\textsubscript{2}, which is similar to previous researches in areas where the concentration level of SO\textsubscript{2} was low \cite{14,15}. Moreover, the emission of SO\textsubscript{2} was mainly related to activities such as coal heating and the demand for heating did not decrease during the COVID-19 outbreak \cite{31}.

### 3.3. Test on parallel trend assumption

DID models require that the experimental and control groups exhibit the same development trend over time \cite{32}, so we examined the parallel trend assumption to determine whether the pollutant concentration trend was parallel before the policy implementation in the control and treatment group. Firstly, it can be seen that the trends of air pollutants before intervention were basically the same in the control group (2019) and the experimental group (2020) before the implementation in

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![Changes in air quality in the BTH region during the Spring Festival in 2019 and 2020](image_url)

**Fig. 1.** Changes in air quality in the BTH region during the Spring Festival in 2019 and 2020. Note: The vertical solid black line represents the start of the Spring Festival. The dashed light-red line represents the end of the Spring Festival in 2019, and the dashed green line indicates the end of the Spring Festival in 2020.
nificant influence on the explanatory variable, the parallel trend of residuals of air quality after eliminating the effects of weather and Fig. 2 shows the time trends 10 days before and after the Spring Festival - Section 3.1 (Fig. 1). Therefore, the parallel trend assumption in this

Note: *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 3
Regression results of the DID model according to Eq. (2).

| Variables | ln(AQI) | ln(PM2.5) | ln(PM10) | ln(SO2) | ln(NO2) | ln(CO) |
|-----------|---------|-----------|----------|---------|---------|--------|
| Corona    | 0.101***| 0.288***  | 0.187*** | 0.239***| 0.511***| 0.151***|
| (0.0331)  | (0.0418) | (0.0399)  | (0.0356) | (0.0285)| (0.0328)|        |
| Holiday   | 0.043    | 0.037     | 0.021    | 0.045   | 0.045** | 0.065**|
|           |         |           |          |         |         |        |
| Other holidays | 0.052** | 0.066**  | 0.032    | 0.044   | 0.074***| 0.075**|
|           |         |           |          |         |         |        |
| Temperature | -0.010***| -0.022***| -0.014***| -0.012***| -0.016***| -0.019***|
|           | (0.0006) | (0.0007) | (0.0007) | (0.0006) | (0.0005) | (0.0006) |
| Humidity  | 0.099*** | 0.017***  | 0.008*** | -0.005***| 0.001*** | 0.009***|
|           | (0.0004) | (0.0005) | (0.0004) |         |         |        |
| Wind speed| -0.047***| -0.097*** | -0.051***| -0.144***| -0.204***| -0.121***|
|           | (0.0072) | (0.0091) | (0.0078) |         |         |        |
| Precipitation | -0.024***| -0.028***| -0.029***| -0.013***| -0.016***| -0.015***|
|           | (0.0014) | (0.0017) | (0.0016) |         |         |        |
| Year      | -0.235***| -0.363*** | -0.315***| -0.145***| -0.052***| -0.127***|
|           | (0.0302) | (0.0381) | (0.0364) |         |         |        |
| Month     | -0.046***| -0.064*** | -0.043***| -0.034***| 0.006*** | -0.038***|
|           | (0.0020) | (0.0025) | (0.0024) |         |         |        |
| Constant  | 478.5*** | 736.9***  | 641.1*** | 296.2***| -101.9* | 255.9***|
|           | (60.91)  | (76.88)   | (73.42)  | (65.53) | (52.51) | (60.34) |
| Observations | 5507     | 5507      | 5507     | 5507    | 5507    |        |
| Within R – squared | 0.237 | 0.398     | 0.211    | 0.263   | 0.428   | 0.379  |

Note: *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2
Panel model regression results according to Eq. (1).

| Variables | ln(AQI) | ln(PM2.5) | ln(PM10) | ln(SO2) | ln(NO2) | ln(CO) |
|-----------|---------|-----------|----------|---------|---------|--------|
| Diff (Corona) | -0.152* | -0.215** | -0.336***| -0.082  | -0.378***| -0.204**|
|           | (0.0659) | (0.1010) | (0.0963) | (0.1160) | (0.0845) | (0.0806) |
| Holiday   | 0.007    | 0.041     | 0.006    | -0.040  | 0.410*** | 0.094* |
|           | (0.0564) | (0.0664) | (0.0632) | (0.0763) | (0.0554) | (0.0529) |
| Treat     | -0.224***| -0.227*** | -0.304***| -0.256***| 0.045    | -0.074 |
|           | (0.0631) | (0.0744) | (0.0707) | (0.0854) | (0.0621) | (0.0592) |
| Temperature | 0.091*** | 0.118***  | 0.112*** | 0.0587***| 0.0695***| 0.064***|
|           | (0.0078) | (0.0092) | (0.00872)| (0.0105) | (0.00766)| (0.0073) |
| Humidity  | 0.022*** | 0.028***  | 0.022*** | 0.004** | 0.009*** | 0.014***|
|           | (0.0012) | (0.0015) | (0.0014) | (0.0017) | (0.0012) | (0.0012) |
| Wind speed| -0.090***| -0.150*** | -0.094***| -0.156***| -0.211***| -0.114***|
|           | (0.0234) | (0.0276) | (0.0262) |         |         |        |
| Precipitation | -0.344***| -0.394***| -0.363***| -0.213***| -0.119***| -0.241***|
|           | (0.0414) | (0.0488) | (0.0464) |         |         |        |
| Constant  | 4.005*** | 3.433***  | 4.162*** | 3.158***| 3.839*** | 0.379***|
|           | (0.0921) | (0.1090) | (0.1030) | (0.1250) | (0.0966) | (0.0465) |
| Observations | 520      | 520       | 520      | 520     | 520     |        |
| R – squared | 0.585    | 0.635     | 0.567    | 0.141   | 0.546   | 0.459  |

Note: *,**,*** indicate significance at the 10%, 5%, and 1% levels, respectively.

Section 3.1 (Fig. 1). Therefore, the parallel trend assumption in this study may be right. In order to better demonstrate the policy impact, we also drew the residual graph of the estimated results of model Eq. (2), Fig. 2 shows the time trends 10 days before and after the Spring Festival of residuals of air quality after eliminating the effects of weather and possible confounding factors. It can be seen that the residuals of both the control group and the experimental group are standardized to a mean of zero [33].

The further counterfactual analysis is carried out by using the following model Eq. (5) to test the parallel trend assumption more strictly [34]. Specifically, we added the interaction terms between the grouping variable Treat and the time trend of the 10 days before the implementation of the control measures to verify the parallel trend of the 10 days before the implementation of the control measures. The beginning of the control measures and the next 2 days were also added to prevent complete collinearity. If the interaction terms of the 10 days before the implementation of the control measures have no significant influence on the explanatory variable, the parallel trend assumption is satisfied.
\[
\ln P_{it} = \delta_0 + \sum_{d=5}^{d_{max}} \delta_1 \text{trend}_d \times \text{Treat} + \sum_{d=10}^{d_{max}} \hat{\delta}_2 \text{trend}_d \\
\times \text{Treat} + \hat{\delta}_3 \text{Holiday} + \theta_{it} W_{it} + \mu_i + \epsilon_{it}
\]  

(5)

where \(d\) represents the days from the implementation of the control measure, \(\text{trend}_d\) represents the time trend, \(\hat{\delta}_1\) represents a series of estimated coefficients for the 10 days before the initiation of the control measures, reflecting the difference in pollutant indicators between the control group and the experimental group as compared to the time before the control measures were implemented.

Table 4 shows the estimated results of Model 5. It can be seen that most of the estimates for the 10 days before the start of the control measures are around zero, and most of the coefficients are not statistically significant. Further, Fig. 3 shows the trend of the estimated coefficients of AQI. We found that the estimated coefficients mostly near the zero value before the implementation of measures, and there is no clear trend. Despite an abnormal down 3 and 4 days before the start of the measures, but then becomes zero value quickly. These results show that the experimental group and control group before the implementation of control measures have the same trend [35].

3.4. Robustness tests

We provide additional evidence to demonstrate that our empirical results were robust. First, we assessed whether our findings remained true if the sample window width was changed. The original sample window in this study involved the 10 days before and after the Spring Festival. We dropped 1–3 days at the head and tail, separately, and re-estimated our model. Our results are reported in Table 5. The directions and magnitudes of coefficients were comparable to our previous findings (i.e., consistent with Table 3).

Subsequently, considering Beijing and Tianjin tightened control measures during the COVID-19 outbreak, we further estimated the robustness of our results by removing Beijing and Tianjin to prevent megacities from interfering with the results. Table 6 shows the effects of the other 11 cities alone. All of the findings were robust to this change (i.e., consistent with Table 3), suggesting that our results were not dominated by the megacities that were most affected by the virus.

4. Heterogeneity: The role of travel restrictions and the intensity of control measures

4.1. Effect of travel restrictions

We first investigated the change in MI, MO, and TI in the BTH region during the Spring Festival in 2019 and 2020 (Fig. 4). Before the Spring Festival, the travel intensity and scale of migration in 2019 and 2020...
were similar, while after the implementation of the regulations in 2020, the travel intensity and migration scale decreased significantly compared with the same period in 2019.

Table 7 shows the empirical results of Model 3. We take the logarithm of the pollutants as the outcomes. It can be seen that the intra-city TI and MO indices demonstrated a significant, positive impact on the NO\textsubscript{2} concentration; One-unit increase in TI in cities increased the NO\textsubscript{2} concentration by 13.6%. However, there was no significant effect on the AQI, PM\textsubscript{2.5}, PM\textsubscript{10}, and CO concentrations. The TI also had a positive effect on the SO\textsubscript{2} concentration; One-unit increase in TI in cities increased the SO\textsubscript{2} concentration by 4%. Two findings of this study are important for future air pollution control in China. First, we found that the restriction measures, especially the control of intra-city TI. As traffic restrictions were gradually lifted at the end of February, anti-epidemic measures on public transportations (e.g., bus and subway) are still strict. This may lead to the increasing use of private cars [36]. Thus calling for a green and safe return towards urban daily traveling is a major concern for the region during a period of unfavourable weather conditions. Human perception on the effectiveness of atmospheric pollution prevention and control measures varied. A scientific, empirical study was needed to quantitatively identify the causal effect of regulatory measures on air quality during the COVID-19 outbreak.

Firstly, the model and estimated result in this study provided an important natural experiment to explore the causal effect of lockdown measures on air quality. Here, real-time monitoring data from China’s air pollution monitoring stations were used to demonstrate air pollutant concentration trends before and after the COVID-19 outbreak, and a DID model was used to estimate the causal effect of the implementation of lockdown measures on air quality, controlling for the interference of meteorological, vacation, and other important factors. The implementation of control measures reduced air pollution, which provided empirical evidence on the identification of the causal effect of lockdown measures on air quality during the COVID-19 outbreak. Two findings of this study are important for future air pollution control. First, we found that the Traffic restrictions, especially the restriction of intra-city TI, were important natural experiment to explore the causal effect of lockdown measures on air quality. Here, real-time monitoring data from China’s air pollution monitoring stations were used to demonstrate air pollutant concentration trends before and after the COVID-19 outbreak, and a DID model was used to estimate the causal effect of the implementation of lockdown measures on air quality, controlling for the interference of meteorological, vacation, and other important factors. The implementation of control measures reduced air pollution, which provided empirical evidence on the identification of the causal effect of lockdown measures on air quality during the COVID-19 outbreak.

Two findings of this study are important for future air pollution control. First, we found that the Traffic restrictions, especially the restriction of intra-city TI, were important for NO\textsubscript{2} pollution control in high-population-density urban regions. This points towards an important direction for future control strategies of NO\textsubscript{2} pollution. Future controls on NO\textsubscript{2} pollution should focus on the control of traffic activities, especially the control of intra-city TI. As traffic restrictions were gradually lifted at the end of February, anti-epidemic measures on public transportations (e.g., bus and subway) are still strict. This may lead to the increasing use of private cars [36]. Thus calling for a green and safe return towards urban daily traveling is a major concern for the region during a period of unfavourable weather conditions. Human perception on the effectiveness of atmospheric pollution prevention and control measures varied. A scientific, empirical study was needed to quantitatively identify the causal effect of regulatory measures on air quality during the COVID-19 outbreak.

Table 8 shows the empirical results of Model 4. The restriction measures displayed a significant, negative effect on the air pollutant concentrations, and for every one-unit increase in the intensity of the control measures, the air pollutant concentration decreased by 2–4%, indicating that the implementation of the restriction measures played a crucial role in improving the atmospheric environment.
government. As individual mobility modes, walking and cycling are desirable under this circumstance. Non-motorised transportation infrastructure for walking and cycling should be continually improved, which will deliver a double benefit to both epidemic prevention and air quality in the long run. In addition, an intra-city TI index system could be established through real-time monitoring of big data systems to achieve accurate control. At the same time, appropriate regulation and incentive mechanisms can be established to reduce the intensity of intra-

Table 7

| Variables   | ln(AQI) | ln(PM2.5) | ln(PM10) | ln(SO2) | ln(NO2) | ln(CO) |
|-------------|---------|-----------|----------|---------|---------|--------|
| TI          | -0.026  | -0.005    | -0.021   | 0.150***| 0.136***| 0.016  |
|             | (0.0263)| (0.0312)  | (0.0292) | (0.0312)| (0.0215)| (0.0243)|
| MI          | -0.002  | -0.004    | -0.007   | -0.049***| 0.011** | -0.019 |
|             | (0.0062)| (0.0074)  | (0.0069) | (0.0074)| (0.0062)| (0.0057)|
| MO         | -0.007  | -0.006    | -0.017*  | -0.040***| 0.015** | -0.016 |
|             | (0.0086)| (0.0102)  | (0.0095) | (0.0102)| (0.0073)| (0.0079)|
| Corona     | -0.451***| -0.477*** | -0.750***| -0.211** | -0.226***| -0.284***|
|             | (0.0761)| (0.0902)  | (0.0845) | (0.0902)| (0.0653)| (0.0701)|
| Holiday    | 0.119** | 0.170**   | 0.190*** | 0.186***| 0.162***| 0.051  |
|             | (0.0563)| (0.0668)  | (0.0625) | (0.0667)| (0.0355)| (0.0519)|
| Temperature| 0.0976***| 0.124***   | 0.122*** | 0.0677***| 0.0772***| 0.0670***|
|             | (0.0072)| (0.0085)  | (0.0080) | (0.0085)| (0.0046)| (0.0066)|
| Humidity   | 0.0205***| 0.0267***  | 0.0203***| -0.00174| 0.00893***|0.013***|
|             | (0.0011)| (0.0013)  | (0.0012) | (0.0013)| (0.0007)| (0.0010)|
| Wind speed | -0.044* | -0.101***  | -0.041   | -0.149***| -0.167***| -0.101***|
|             | (0.0237)| (0.0281)  | (0.0263) | (0.0281)| (0.0081)| (0.0214)|
| Precipitation| -0.337***| -0.376***  | -0.345***| -0.136***| -0.128***| -0.238***|
|             | (0.0413)| (0.0490)  | (0.0458) | (0.0489)| (0.0299)| (0.0380)|
| Constant   | 4.032***| 3.372***   | 4.196*** | 2.868***| 2.976***| 0.066***|
|             | (0.1490)| (0.1770)  | (0.1650) | (0.1770)| (0.1040)| (0.1370)|
| Observations| 520     | 520       | 520      | 520     | 520     | 520    |
| R squared   | 0.582   | 0.633     | 0.571    | 0.369   | 0.559   | 0.497  |

Note: *, **, *** indicate significance at 10%, 5%, and 1% levels, respectively.
city travel, such as traffic restrictions of tail numbers, oil price increases, public transportation subsidies, and so on [37,38]. Secondly, our study quantified the improvement of air pollution with a differentiated intensity of control measures in the BTH region. We have made a pioneering quantification of the control measures and found that the intensity of control measures had a significant effect on air pollution. It has important significance for the formulation of accurate and effective socio-economic measures. As a densely populated area with severe air pollution in China, the BTH region has a huge scale of economic activities and energy consumption [39]. The economic cost will be huge if population mobility and industrial activities are unreasonably restricted, so it is important to establish appropriate, flexible, and sustainable measures for air pollution control. Based on our results, it would be helpful to improve the effectiveness of air pollution control by establishing refined and intelligent hierarchical control measures for economic and social activities and policies for energy conservation and emission reduction [26]. For further control of air pollution in the BTH region, classified control measures could be established according to the causal effect of lockdown measures on air pollution concentration and emission reduction targets, and different means combinations and implementation methods could be carried out to adapt to the classification system of different pollutant levels.

Finally, this study also investigated the experimental significance of control measures for the reduction of extreme air pollution. The COVID-19 outbreak is a special public health event due to its particularity and uncertainty and provides an extremely rare natural experiment in the control of social and economic activities affecting air pollution. There are massive pollution outbreak events in northern China, especially in the BTH region, such as winter fog haze pollution. Extreme air pollution harms human health and the social economy, especially in densely populated and economically developed urban agglomerations [19,40]. Therefore, high-intensity restrictions on population, traffic, and economic activities should be taken to reduce its harm to deal with extreme air pollution. For example, when an extreme air pollution event occurs, the teleworking and online-education system developed during the COVID-19 lockdown will immediately be used. Our research has provided important evidence for contingency planning on integrated socio-economic control measures in extreme pollution situations.

6. Conclusions

Determining the causal effect of control measures on air pollution during the COVID-19 outbreak is an important issue. Here, we quantitatively identified the causal effect of lockdown measures on air quality in the BTH region by building a DID model. We not only found that lockdown measures had a significant positive effect on air quality, but also discovered the heterogeneous effects of lockdown measures. As was expected, the implementation of control measures reduced the AQI decreased by 15.2%, NO2 decreased by 37.8%, followed by PM10, PM2.5, and CO, which decreased by 33.6%, 21.5%, and 20.4%, respectively. Further study showed that traffic restrictions, especially the restriction of intra-city travel intensity (TI), had a significant and heterogeneous effect on NO2 with a concentration decrease of approximately 13.6%. Moreover, we conducted a study on the intensity of the control measures and found that every one-unit increase in the intensity of control reduced the air pollutant concentration by approximately 2–4%.

Our study focuses on air pollution reduction caused by the suspension of human-related energy activities during the COVID-19 lockdown. These findings had important implications for reducing air pollution, and would help policymakers to implement differentiated management policies for different air pollution situations [41]. We found that the management of traffic activities was important for NO2 pollution control in high-population-density urban regions, especially the intra-city travel intensity (TI). Thus the safe individual mobility should be promoted to make an environmentally friendly recovery. And big data and artificial intelligence can be used to accurately achieve air pollution control. Moreover, high-intensity restrictions on population, traffic, and economic activity are important to deal with extreme air pollution in cities. This study provides important evidence for developing emergency plans for comprehensive social and economic control measures in extreme pollution situations by estimating the differentiated effects on air pollution reduction induced by different high-intensity control measures.

Based on above findings, we highlighted the importance of green commuting and intelligent hierarchical control measures for both energy conservation and emission reduction, which is conducive to the future green recovery of transport and energy system. Moreover, China is the country with the earliest outbreak of COVID-19 and the most drastic quarantine measures. The heterogeneous effects of COVID-19 lockdown on air quality in northern China have reference significance from international perspectives.

It is necessary to point out two areas for further study. Although there was an unprecedented improvement in air quality as a result of the control measures, air pollution during the lockdown maintained a high level. Other sources of air pollution such as coal-fired winter heating systems and adverse meteorological factors may have contributed to air pollutant concentrations [42,43]. Secondly, the positive effect on air quality was temporary, as studies have found that the control measures during the COVID-19 outbreak have only improved China’s air quality in the short term. However, massive energy use and industrial activity may lead to higher air pollution levels when the COVID-19 outbreak

| Variables | ln(\text{AQI}) | ln(\text{PM2.5}) | ln(\text{PM10}) | ln(\text{SO2}) | ln(\text{NO2}) | ln(\text{CO}) |
|-----------|---------------|-----------------|-----------------|----------------|----------------|---------------|
| Control   | -0.025***     | -0.028***       | -0.043***       | -0.023***      | -0.193***      | -0.013***     |
|           | (0.0040)      | (0.0046)        | (0.0044)        | (0.0053)       | (0.0038)       | (0.0037)      |
| Holiday   | 0.121**       | 0.153***        | 0.181***        | 0.089**        | 0.482***       | 0.098**       |
|           | (0.0477)      | (0.0562)        | (0.0532)        | (0.0644)       | (0.0458)       | (0.0448)      |
| Temperature | 0.101***     | 0.127***        | 0.129***        | 0.071***       | 0.080***       | 0.066***      |
|           | (0.0074)      | (0.0087)        | (0.0082)        | (0.0099)       | (0.0071)       | (0.0069)      |
| Humidity  | 0.020***      | 0.026***        | 0.020***        | 0.002***       | 0.009***       | 0.013***      |
|           | (0.0010)      | (0.0012)        | (0.0012)        | (0.0014)       | (0.0010)       | (0.0010)      |
| Wind speed | -0.092***    | -0.152***       | -0.103***       | -0.155***      | -0.245***      | -0.113***     |
|           | (0.0234)      | (0.0276)        | (0.0261)        | (0.0316)       | (0.0225)       | (0.0220)      |
| Precipitation | -0.301*** | -0.344***      | -0.296***       | -0.166***      | -0.130***      | -0.234***     |
|           | (0.0416)      | (0.0489)        | (0.0463)        | (0.0561)       | (0.0399)       | (0.0390)      |
| Constant  | 4.048***      | 3.479***        | 4.229***        | 3.196***       | 3.970***       | 4.048***      |
|           | (0.0935)      | (0.1100)        | (0.1040)        | (0.1260)       | (0.0897)       | (0.0878)      |
| Observations | 520          | 520             | 520             | 520            | 520            | 520           |
| R-squared | 0.578         | 0.631           | 0.566           | 0.134          | 0.562          | 0.450         |

Note: *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively.
control measures are removed over the long term [44]. A significant challenge remains to maintain this improvement in air quality.

Finally, since air pollution occurs in line with human activities, prevention and control of air pollution is a long-term battle. Although the extreme control measures of public emergencies such as the COVID-19 outbreak have demonstrated an improvement in air quality, they caused significant damage to society and the economy. Therefore, the formulation of sustainable development measures that consider economic, social, and environmental aspects is the key to the long-term control of air pollution in the BTH region [36,45].

CRediT authorship contribution statement

Junfeng Wang: Conceptualization, Methodology, Writing - original draft, Writing - review & editing. Xiaoya Xu: Writing - original draft. Shimeng Wang: Writing - original draft. Shutong He: Writing - review & editing. Pan He: Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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