Diverse spillover effects of COVID-19 control measures on air quality improvement: evidence from typical Chinese cities

Laijun Zhao1 · Yu Wang1 · Honghao Zhang1 · Ying Qian1 · Pingle Yang1 · Lixin Zhou1

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Abstract
The COVID-19 prevention and control measures are taken by China’s government, especially traffic restrictions and production suspension, had spillover effects on air quality improvement. These effects differed among cities, but these differences have not been adequately studied. To provide more knowledge, we studied the air quality index (AQI) and five air pollutants (PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, and O$_3$) before and after the COVID-19 outbreak in Shanghai, Wuhan, and Tangshan. The pollution data from two types of monitoring stations (traffic and non-traffic stations) were separately compared and evaluated. We used monitoring data from the traffic stations to study the emission reduction caused by traffic restrictions. Based on monitoring data from the non-traffic stations, we established a difference-in-difference model to study the emission reduction caused by production suspension. The COVID-19 control measures reduced AQI and the concentrations of all pollutants except O$_3$ (which increased greatly), but the magnitude of the changes differed among the three cities. The control measures improved air quality most in Wuhan, followed by Shanghai and then Tangshan. We investigated the reasons for these differences and found that differences in the characteristics of these three types of cities could explain these differences in spillover effects. Understanding these differences could provide some guidance and support for formulating differentiated air pollution control measures in different cities. For example, whole-process emission reduction technology should be adopted in cities with the concentrated distribution of continuous process enterprises, whereas vehicles that use cleaner energy and public transport should be vigorously promoted in cities with high traffic development level.

Keywords Spillover effect · COVID-19 · Traffic restrictions · Production suspension · Difference-in-difference model
1 Introduction

The COVID-19 pandemic has caused serious global economic and health crises (Mousazadeh et al., 2021; Sohrabi et al., 2020). To prevent the spread of COVID-19, governments around the world have taken strict prevention and control measures. On January 23, 2020, Wuhan, a major city in central China, took the lead in implementing lockdown measures. Subsequently, other Chinese provinces and cities adopted a series of strict COVID-19 prevention and control measures. Although these measures greatly affected the daily lives of citizens, they also brought unexpected "benefits," such as improved air quality in many cities (Benchrif et al., 2021; Filonchyk et al., 2020; Gope et al., 2021; Pei et al., 2020; Zhou et al., 2021). However, the air quality improvement has been greater in some cities than in others, and some cities have even experienced worsened air quality (Le et al., 2020). The pandemic can thus be regarded as an unprecedented and unplanned experiment. On the one hand, it lets us test the feasibility of previous pollution control work; on the other hand, the potential air quality improvement in each city can be evaluated to provide a basis for formulating future air pollution control plans.

Many scholars have studied the impact of COVID-19 on air quality in Chinese cities. The pandemic began in Wuhan, so most scholars focused their attention on Wuhan. Jiaxin et al. (2021) found that Wuhan’s air quality in 2020 improved by 17.6% to 20.1% compared with the previous three years. Sulaymon et al. (2021) investigated changes in the concentrations of six air pollutants (PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, CO, and O$_3$) in Wuhan before, during, and after the COVID-19 lockdown period. They found that the concentrations of air pollutants decreased significantly compared with the values before the pandemic, but that the concentration of O$_3$ increased by 149% during the lockdown. The air quality in most other Chinese cities also improved during the lockdown. PM$_{2.5}$, PM$_{10}$, SO$_2$, and NO$_x$ decreased by 30% to 50% compared to the values before pre-Level I period in southwestern China (Chen et al., 2020). The emission reduction was less obvious in northern China than in southern China possibly because of the need to burn coal to generate warmth during many months of the year. The concentrations of SO$_2$, PM$_{2.5}$, PM$_{10}$, NO$_2$, and CO decreased by 6.8%, 5.9%, 13.7%, 24.7%, and 4.6%, respectively, during the lockdown period in 44 cities in northern China (Bao & Zhang, 2020). The spillover effects of COVID-19 prevention and control measures on air quality in China were not always positive (Li et al., 2021). Severe PM$_{2.5}$ pollution occurred in Nanning, which is located in the Guangxi province of southern China, during the lockdown (Mo et al., 2021). The improvement in air quality caused by COVID-19 responses has also been seen around the world (He et al., 2021). In California, the USA, levels of NO$_2$, CO, and PM$_{2.5}$ dropped by 38%, 49%, and 31%, respectively, during the lockdown compared with historical averages from 2015 to 2019 (Liu et al., 2020). In France, the maximum daily concentrations detected in different regions have decreased by 18.18%, 37.14%, 20.36%, 5.1%, and 44.38%, respectively, for the pollutants SO$_2$, NO$_2$, CO, PM$_{2.5}$ and PM$_{10}$ (Ikhlasse et al., 2021). In India, PM$_{10}$ and PM$_{2.5}$ concentrations decreased by approximately 48.56% and 57.09%, respectively, compared to the previous four years across the country (Pal et al., 2021). However, air quality worsened in some countries during the lockdown. The concentration of SO$_3$ increased in both Seoul and Tokyo due to the effect of transporting from polluted upwind regions (Ghahremanloo et al., 2021). In Thailand, the concentration of NO$_2$ increased by 47.4% during the COVID-19 pandemic (Oo et al., 2021).

Traffic restrictions and production suspension have a significant positive impact on air quality (Jevtic et al., 2021). During the lockdown, road traffic in Beijing reduced by...
46.9%, while the concentrations of PM$_{2.5}$ and NO$_2$ reduced by 5.6% and 29.2%, respectively. The maximum possible contribution rate of road traffic to PM$_{2.5}$ and NO$_2$ concentrations is 11.9% and 62.3%, respectively (Xin et al., 2021). Chen et al. (2021) analyzed the effects of private vehicle restriction policies on air pollution and found that the private vehicle restriction policies reduce the degree of air pollution to a certain extent. Wang, Yuan, et al. (2020) believed the transportation sector was related to the NO$_2$ emission reductions, while lower emissions from secondary industries were the major cause for the reductions of PM$_{2.5}$ and CO. The reduction in SO$_2$ concentrations was only linked to the industrial sector. Tang et al., (2021) explored whether this epidemic has a great impact on air pollution and conclude shutting down heavy industry factories is one of the top effective policies to reduce air pollution. Reductions in industrial operations and constructions in operations led to lowered SO$_2$, NO$_x$, PM$_{2.5}$, and VOCs emissions by approximately 16%–26%, 29%–47%, 27%–46%, and 37%–57% over the Yangtze River Delta Region (Li et al., 2020).

These studies mainly focused on the overall changes of pollutant concentrations during the COVID-19 lockdown. However, few studies considered the differences in spillover effects among different types of cities and attempted to explain the reasons behind these differences. Given that the traffic development level and the industrial structure differ greatly among cities, the COVID-19 prevention and control measures can be expected to have different impacts on the pollutant emission of different cities, leading to different impacts on the air quality. In this paper, three typical Chinese cities with different traffic and industrial characteristics were selected to study the differences of spillover effects of traffic restrictions and production suspension on air quality improvement. Specifically, we hypothesized that the differences among the cities would lead to different responses of air pollution to the lockdown measures. By analyzing the reasons behind the differences among these cities, we are able to provide policy suggestions and guidance for future air pollution control work.

After the outbreak of the COVID-19 pandemic, scholars have used a variety of methods to study the impact of the COVID-19 pandemic on air quality. Some scholars compared the concentrations of air pollutants before and after the outbreak of the COVID-19 pandemic (Tobias et al., 2020; Rodriguez-Urrego & Rodriguez-Urrego, 2020). This method does not consider the influence of climate factors on pollutant concentrations, which will bring some deviations to the research results. Some scholars used multiple linear regression, generalized additive model (GAM) to predict pollutant concentrations in the business as usual (BAU) scenario and compared the results with the actual observed concentrations during COVID-19 lockdown (Gonzalez-Pardo et al., 2022; Dacre et al., 2020; Solberg et al., 2021). However, they did not verify the accuracy of the predicted results, which may result in inaccurate conclusions. Some researchers used the Community Multi-scale Air Quality model (CMAQ) to simulate pollutant concentrations during the lockdown period and compared them with observed concentrations (Liu, Wang, et al., 2021; Wang, Chen, et al., 2020). However, the CMAQ has a systematic error (i.e., simulated data are smaller than observed data) (Wang et al., 2013), which may amplify the impact of the COVID-19 pandemic on air quality. Also, some scholars used the DID model to study the impact of the COVID-19 pandemic on air quality (Ming et al., 2020; Zhang et al., 2021). Based on monitoring data from the non-traffic stations, this paper established a DID model to study the impact of production suspension on air quality. Compared with the methods used in the above-mentioned studies, the DID model can not only take meteorological factors as control variables to avoid their influence on the research results, but also control the systematic differences...
between the treatment group (2020) and the control group (2019), thus ensuring the accuracy of the research results.

The remainder of this article is structured as follows. Section 2 introduces the temporal and spatial characteristics of the samples, the data sources, and our analytical methods. Section 3 presents the differences in the spillover effects of traffic restrictions and production suspension. Section 4 discusses the reasons for these differences. Section 5 summarizes our findings and provides policy suggestions and support for future air pollution control work.

2 Materials and methods

2.1 Temporal and spatial samples

To curb the spread of COVID-19, China’s provinces gradually implemented first-level public health emergency response (Level I Response) on January 23, 2020, and Wuhan was the first city in China to implement a full lockdown. During the Level I Response period, the government implemented specific prevention and control measures that included vehicle traffic restrictions (i.e., a ban on travel in all vehicles except public transport) and production suspension (except for essential industries such as electric power generation and steel plants). As the COVID-19 outbreak was gradually controlled, all provinces lowered the response level (i.e., eliminating traffic restrictions and full resumption of production). On this basis, we chose January 23, 2020, as the dividing line between the pre-pandemic and post-pandemic periods to study the changes of air quality. We selected the period from November 10, 2019, to January 23, 2020 (T1) and the period from January 24, 2020, to the date of lowering the response level (T2) as temporal samples. For our comparative analysis, we selected the same periods in the previous year as reference time periods and denoted these periods as RT1 and RT2, respectively. Table 1 summarizes the time periods.

The reasons for choosing the sample periods according to the solar calendar time are as follows. Firstly, a very important reason for choosing the sample period according to the solar calendar time is to avoid the influence of climatic differences on the study results. Since there is a large difference between the dates of the solar calendar and the lunar calendar, choosing the sample periods according to the lunar calendar would result in a relatively large difference in climatic and environmental conditions between the sample period in 2020 and its counterpart in 2019, which would bring a significant deviation to the results. Choosing the sample periods according to the solar calendar can ensure the relatively stable climatic and environmental conditions of the two sample periods, thus avoiding the deviation caused by climate factors. Besides, continuous process enterprise, such

|          | Shanghai                  | Wuhan                    | Tangshan                  |
|----------|---------------------------|--------------------------|---------------------------|
| T1       | 10 Nov 2019–23 Jan 2020   | 10 Nov 2019–23 Jan 2020  | 10 Nov 2019–23 Jan 2020  |
| T2       | 24 Jan 2020–24 Mar 2020   | 24 Jan 2020–9 Apr 2020   | 24 Jan 2020–30 Apr 2020  |
| RT1      | 10 Nov 2018–23 Jan 2019   | 10 Nov 2018–23 Jan 2019  | 10 Nov 2018–23 Jan 2019  |
| RT2      | 24 Jan 19 Jan 2019–24 Mar 2019 | 24 Jan 19 Jan 2019–9 Apr 2019 | 24 Jan 19 Jan 2019–30 Apr 2019 |
as steel plants and thermal power plants, did not suspend their production during either
the Chinese New Year holiday or the Level I Response period. Most international logistics
and international trade continue during the Chinese New Year holiday. Only the service
industry related to people’s daily lives, such as the catering industry, partly suspend during
the Chinese New Year holiday in cities because people left for their hometowns. But
these industries account for a small percentage of pollution emissions. Therefore, production
suspension during the Chinese New Year holiday will not bring a substantial deviation
to the results of this paper.

Wuhan was the city most severely hit by COVID-19 and has almost taken a complete
lockdown to prevent the spread of the COVID-19 pandemic at the beginning of 2020. It is
of great significance to study the impact of COVID-19 control measures on air quality in
Wuhan. Therefore, Wuhan was chosen as a representative of the cities which were severely
hit by the COVID-19 pandemic. Shanghai is the largest city in China with a total population
of 24.882 million and has a well-developed tertiary industry. In 2019, the output value
of the tertiary industry in Shanghai was 2775.228 billion, accounting for 72.7% of GDP,
exceeding the total GDP of most cities in China. In addition, Shanghai has a highly devel-
oped logistics industry and is the most important port city in China. In 2019, Shanghai’s
international standard container throughput was 43.303 million TEU, ranking first in the
world. The tertiary industry and logistics industry suspended operations during the Level
I Response period. Therefore, we choose Shanghai as the typical representative of the cit-
ies where major portion of production suspended. Tangshan is a typical industrial city in
China, with the secondary industry accounting for 52.4% of GDP in 2019. Tangshan’s sec-
ondary industry is mainly continuous process enterprises, such as steel plants and cement
plants. Tangshan’s steel production accounted for 13.7% of the total national production in
2019. The production of pig iron, crude steel, and finished steel was 122.78 million tons,
136.89 million tons, and 150.94 million tons, accounting for 15.2%, 13.7%, and 12.5% of
the national total production, respectively. These enterprises did not stop operation during
the Level I Response period. Therefore, we choose Tangshan as a typical representative of
the cities where limited portion of production suspended.

2.2 Data sources

From the National Air Quality Real-time Publishing Platform (https://air.cnemc.cn:18007),
we collected the daily AQI and the daily average concentrations of five air pollutants (PM$_{2.5}$,
PM$_{10}$, SO$_2$, NO$_2$, and O$_3$) in Shanghai, Wuhan, and Tangshan. AQI is calculated as follows:

\[
\text{IAQI}_{pi} = \frac{I_H - I_L}{C_H - C_L} (x_{pi} - C_L) + I_L
\]

where IAQA$_{pi}$ and $x_{pi}$ are the IAQA and the daily mean concentration of pollutant $p$ on day
$i$; $C_H$ and $C_L$ are the upper and lower limits of a given pollutant’s concentration. $I_H$ and $I_L$
are the IAQAs corresponding to $C_H$ and $C_L$, respectively. The maximum IAQA for five pol-
lutants in a given day is defined as the AQI for that day.

There are 26 stations in the three cities (Fig. 1). For Shanghai, data from 10 stations,
only PT, HK, XH, YP, QP, JA, CS, ZJ, SWC, and PDXQ. For Wuhan, data from 10 stations,
only DH, HY, WC, TK, HKJT, DHGX, WJS, CH, HK, and QS. For Tangshan, data from 6 stations,
only LDZ, WZJ, TCGS, SEZ, XS, and GXS. Table 2 shows the specific spatial information of each station. We also obtained meteorological data for
Including temperature, wind speed, relative humidity, atmospheric pressure, and precipitation. We examined the correlation between each of the meteorological factors. The results in Table 3 showed that the correlation coefficients between each of the meteorological factors are very small. This means that each meteorological factor is not highly correlated with the other and does not represent similar driving forces. Table 4 presents the summary statistics of our key variables.

### 2.3 Methods

We calculated the overall changes of the air pollutant concentrations in Shanghai, Wuhan, and Tangshan during Level I Response period using the average value of the monitoring
data at all stations. The two most important prevention and control measures during this period were traffic restrictions and production suspension. Therefore, we will separately study the impact of traffic restrictions and production suspension on air quality in Shanghai, Wuhan, and Tangshan.

To study the impact of traffic restrictions on the air quality during the Level I Response period, the monitoring stations in each city were divided into traffic and non-traffic stations (Lau et al., 2008). PDXQ and SWC stations in Shanghai, HK and QS stations in Wuhan,

Table 3  The correlations between each of the meteorological factors in Shanghai, Wuhan, and Tangshan

| City   | Meteorological factors | Wind speed | Precipitation | Atmospheric pressure | Relative humidity | Temperature |
|--------|------------------------|------------|---------------|----------------------|-------------------|-------------|
| Shanghai | Wind speed            | 1          | 0.201         | 0.032                | −0.033            | −0.03       |
|         | Precipitation         | 0.201      | 1             | −0.112               | 0.552             | 0.009       |
|         | Atmospheric pressure  | 0.032      | −0.112        | 1                    | −0.202            | −0.499      |
|         | Relative humidity     | −0.033     | 0.552         | −0.202               | 1                 | 0.089       |
|         | Temperature           | −0.03      | 0.009         | −0.499               | 0.089             | 1           |
| Wuhan   | Wind speed            | 1          | 0.348         | 0.005                | 0.098             | −0.017      |
|         | Precipitation         | 0.348      | 1             | −0.019               | 0.459             | −0.099      |
|         | Atmospheric pressure  | 0.005      | −0.019        | 1                    | 0.001             | −0.575      |
|         | Relative humidity     | 0.098      | 0.459         | 0.001                | 1                 | −0.231      |
|         | Temperature           | −0.017     | −0.099        | −0.575               | −0.231            | 1           |
| Tangshan| Wind speed            | 1          | −0.029        | −0.262               | −0.379            | 0.316       |
|         | Precipitation         | −0.029     | 1             | −0.111               | 0.321             | 0.093       |
|         | Atmospheric pressure  | −0.262     | −0.111        | 1                    | −0.029            | −0.64       |
|         | Relative humidity     | −0.379     | 0.321         | −0.029               | 1                 | −0.061      |
|         | Temperature           | 0.316      | 0.093         | −0.64                | −0.061            | 1           |

Table 4  Summary statistics on values of the air pollutants and meteorological factors

| Variables   | Obs | Units   | Mean  | Std.Dev | Min  | Max  |
|-------------|-----|---------|-------|---------|------|------|
| AQI         | 7810| N/A     | 78.95 | 44.85   | 14   | 368  |
| PM_{2.5}    | 7810| μg/m^3 | 55.02 | 37.19   | 3    | 296  |
| PM_{10}     | 7810| μg/m^3 | 80.09 | 52.39   | 2    | 454  |
| SO_{2}      | 7810| μg/m^3 | 12.70 | 11.56   | 1    | 102  |
| NO_{2}      | 7810| μg/m^3 | 46.30 | 21.80   | 2    | 138  |
| O_{3}       | 7810| μg/m^3 | 44.95 | 23.93   | 2    | 162  |
| Temperature | 7810| °C      | 7.27  | 6.06    | −11.70 | 26.60 |
| Humidity    | 7810| %       | 70.66 | 17.82   | 17.00 | 100.00 |
| Wind speed  | 7810| m/s     | 1.72  | 1.02    | 0.00  | 7.50  |
| Atmospheric pressure | 7810| hpa | 1022.58 | 6.74 | 999.00 | 1041.00 |
| Precipitation | 7810| mm     | 2.09  | 4.97    | 0.00  | 31.90 |
and GXS station in Tangshan were traffic stations. The changes of air quality at the traffic stations during T2 compared with T1 and with RT2 can be calculated as follows:

\[ P_1 = \frac{C_{T2} - C_{T1}}{C_{T1}} \times 100\% \]  
\[ P_2 = \frac{C_{T2} - C_{RT2}}{C_{RT2}} \times 100\% \]

where \( C \) is the mean pollutant concentration in the specified period.

We then need to measure the impact of the production suspension on air quality based on the data from the non-traffic stations. However, meteorological factors and the Spring Festival holiday have an impact on air quality. Therefore, wind speed, precipitation, atmospheric pressure, relative humidity, temperature, and the Spring Festival holiday should be controlled to evaluate the effect of production suspension. Endogenous problems occur when reverse causality occurs between the variables or some variables are missing (Wan et al., 2019). Therefore, we use the DID method in this paper because it is powerful to avoid the endogenous problems that typically arise. Furthermore, the DID model can control the systematic differences between the treatment and control groups and remove the biases that could be caused by other variables (i.e., missing variables). The DID model is as follows:

\[ \ln P_{it} = \alpha_0 + \alpha_1 \text{IND} \times \text{Treat} + \theta_1 X_{it} + \theta_2 \text{Holiday} + \mu_i + \pi_t + \epsilon_{it} \]

where the subscript \( i \) represents the \( i \)th monitoring station, and subscript \( t \) represents the date. \( \ln P_{it} \) is the logarithm of the mean pollutant concentration (AQI, PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, and O$_3$) at station \( i \) on day \( t \). \( \alpha_0 \) represents the y-intercept. \( \text{IND} \) is a dummy variable that is set to 1 if it is after the production suspension (23 January) or 0 otherwise. \( \text{Treat} \) is the group dummy variable. It is set to 1 if it is in the treatment group (2020) and set to 0 for the control group (2019). \( X_{it} \) is a series of meteorological control variables (wind speed, precipitation, atmospheric pressure, relative humidity, and temperature). \( \text{Holiday} \) is a dummy variable that is set to 1 if it is during the Spring Festival holiday (2019.2.4–2019.2.10 or 2021.1.24–2020.2.2), and 0 otherwise. \( \mu_i \) is individual fixed effects. \( \pi_t \) indicates date fixed effects. \( \epsilon_{it} \) is the stochastic error term.

3 Results

3.1 Changes of pollutant concentrations at all stations during level I response period

We obtained the mean pollutants concentrations by averaging data from all monitoring stations in Shanghai, Wuhan, and Tangshan (Fig. 2, 3, and 4, respectively). During the T2 period, AQI was the highest in Tangshan (86.1), followed by Wuhan (55.3) and Shanghai (49.6). The highest PM$_{2.5}$ and PM$_{10}$ concentrations were recorded in Tangshan (55.9 µg/m$^3$ and 96.8 µg/m$^3$, respectively), followed by Wuhan (37.0 µg/m$^3$ and 52.2 µg/m$^3$) and Shanghai (34.3 µg/m$^3$ and 41.7 µg/m$^3$). The highest SO$_2$ concentrations occurred in Tangshan (19.4 µg/m$^3$), followed by Wuhan (8.09 µg/m$^3$) and Shanghai (6.1 µg/m$^3$). NO$_2$ was highest in Tangshan (41.4 µg/m$^3$), followed by Shanghai (29.9 µg/m$^3$) and Wuhan (21.3 µg/
Diverse spillover effects of COVID-19 control measures on air... m$^3$). Finally, the O$_3$ concentration was 73.2 μg/m$^3$ in Shanghai, followed by 64.3 μg/m$^3$ in Wuhan, and 56.9 μg/m$^3$ in Tangshan.

To analyze air quality after the COVID-19 outbreak, we compared the pollutant concentrations in the T2 period with those in periods T1 and RT2, respectively, and calculated the changes in the pollutant concentrations. When comparing the pollutant concentrations...
in the T2 period with those in the T1 period, AQI decreased by 20.0% in Shanghai, 32.6% in Wuhan, and 14.8% in Tangshan. Wuhan’s PM$_{2.5}$ and PM$_{10}$ concentrations decreased the most, by 36.0% and 39.3%, respectively. Although PM$_{2.5}$ and PM$_{10}$ also decreased in Shanghai, the percentages were lower, by 25.4% and 26.5%, respectively. The PM$_{2.5}$ and PM$_{10}$ concentrations in Tangshan decreased the least, by 13.1% and 19.3%, respectively. The SO$_2$ concentrations in Shanghai, Wuhan, and Tangshan decreased by 21.9%, 17.6%, and 23.9%, respectively. The largest reduction in the NO$_2$ concentration occurred in Wuhan (59.1%), followed by Shanghai (45.7%) and Tangshan (30.8%). Unfortunately, the O$_3$ concentration increased from T1 to T2 for all three cities: by 76.0% for Shanghai, 143.6% for Wuhan, and 199.5% for Tangshan.

These percentages show that the government’s COVID-19 prevention and control measures significantly improved most aspects of the air quality, with the exception of O$_3$. Although the pollutant concentrations in the same period in the reference year also decreased (RT2 versus RT1), the percentage decrease was much smaller than the decrease from T1 to T2.

When comparing the pollutant concentrations in the T2 period with those in the RT2 period, the AQI in Shanghai and Wuhan decreased by 26.3% and 33.1%, respectively, whereas that in Tangshan decreased by 8.8%. Shanghai’s PM$_{2.5}$ and PM$_{10}$ decreased by 23.6% and 26.7%, respectively. Wuhan’s PM$_{2.5}$ and PM$_{10}$ decreased by 35.8% and 36.3%, respectively, which represents the largest decrease among the three cities. Tangshan’s PM$_{2.5}$ decreased by 6.7%, and its PM$_{10}$ decreased by 14.3%. The SO$_2$ concentrations in Shanghai, Wuhan, and Tangshan decreased by 11.3%, 8.0%, and 17.1%, respectively. NO$_2$ decreased by 30.3% in Shanghai, 51.8% in Wuhan, and 16.0% in Tangshan. O$_3$ increased again in all three cities, but by lower percentages: 11.9% for Shanghai, 46.5% for Wuhan, and 9.8% for Tangshan.

These comparisons reveal that the air quality in Shanghai and Wuhan improved significantly, except for O$_3$ levels, whereas the air quality in Tangshan improved less obviously.
However, the COVID-19 prevention and control measures greatly increased O₃ pollution in the three cities.

### 3.2 Impact of traffic restrictions on air quality

The 5-day average pollutant concentrations at the traffic stations are shown in Figs. 5, 6, and 7, respectively. During the T2 period, the highest mean AQI appeared in Tangshan (82.2), followed by Wuhan (64.3) and Shanghai (47.3). The PM₂.₅ concentration was 32.8 μg/m³ in Shanghai, 45.0 μg/m³ in Wuhan, and 53.1 μg/m³ in Tangshan. The highest PM₁₀ concentration was recorded in Tangshan (89.7 μg/m³), followed by Wuhan (56.1 μg/m³) and Shanghai (39.1 μg/m³). The SO₂ concentrations were 5.1 μg/m³, 8.5 μg/m³, and 18.1 μg/m³ in Shanghai, Wuhan, and Tangshan, respectively. The lowest NO₂ concentration was recorded in Wuhan (25.8 μg/m³), and the highest in Tangshan (41.2 μg/m³), with an intermediate value of 26.2 μg/m³ in Shanghai. Finally, the O₃ concentration is 73.3 μg/m³, 65.4 μg/m³, and 57.2 μg/m³ in Shanghai, Wuhan, and Tangshan, respectively.

When we compare pollutant concentrations in the T2 period with those in the T1 period, Wuhan’s AQI decreased most (30.3%), followed by Shanghai (24.6%) and then Tangshan (15.3%). Shanghai’s PM₂.₅ and PM₁₀ decreased by 26.9% and 26.7%, respectively, versus 33.3% and 36.4% in Wuhan and 20.8% and 19.4% in Tangshan. Shanghai’s SO₂ decreased by 30%, Wuhan’s by 5.2%, and Tangshan’s by 23.6%. NO₂ was the most strongly affected by the traffic restrictions. The NO₂ concentrations in Shanghai, Wuhan, and Tangshan decreased by 49.9%, 54.9%, and 32.4%, respectively. The O₃ concentration increased most in Tangshan (189.9%), followed by Wuhan (175.0%) and Shanghai (79.1%).

![Fig. 5 The 5-day average pollutant concentrations at Shanghai’s traffic stations during T1, T2, RT1, and RT2. Red dashed line represents the date of pandemic outbreak](image-url)
Fig. 6 The 5-day average pollutant concentrations at Wuhan’s traffic stations during T1, T2, RT1, and RT2. Red dashed line represents the date of pandemic outbreak.

Fig. 7 The 5-day average pollutant concentrations at Tangshan’s traffic stations during T1, T2, RT1, and RT2. Red dashed line represents the date of pandemic outbreak.
Compared with the RT2 period, the air quality at the traffic stations during the T2 period was also better than that in the same period of the previous year. AQI decreased by 28.6% in Wuhan, 26.0% in Shanghai, and 13.8% in Tangshan. PM$_{2.5}$, PM$_{10}$, and NO$_2$ concentrations in Wuhan also decreased greatly, by 31.1%, 35.8%, and 45.1%, respectively. PM$_{2.5}$, PM$_{10}$, and NO$_2$ in Shanghai decreased by 21.8%, 27.4%, and 36.3%, respectively. PM$_{2.5}$, PM$_{10}$, and NO$_2$ in Tangshan decreased the least among the three cities, by 13.3%, 19.3%, and 20.7%, respectively. SO$_2$ decreased the most in Shanghai (39.9%), followed by Tangshan (10.7%) and Wuhan (9.7%). The O$_3$ concentration increased by 54.7% in Wuhan, 17.9% in Shanghai and 9.3% in Tangshan.

During the T2 period, the pollutant concentrations at the traffic stations decreased greatly compared with both the T1 and the RT2 periods. However, the O$_3$ concentration unexpectedly increased. Although traffic restrictions greatly improved the air quality, they also resulted in severe O$_3$ pollution, which is a problem that requires attention.

### 3.3 Impact of the production suspension on air quality

#### 3.3.1 Empirical results

We developed a DID model to measure the impact of production suspension on air quality. Tables 5, 6, and 7 show the model results for Shanghai, Wuhan, and Tangshan, respectively. In Shanghai, the production suspension policy reduced AQI and the PM$_{2.5}$, PM$_{10}$, SO$_2$, and NO$_2$ concentrations by 18.9%, 29.5%, 31.3%, 30.8%, and 55.3%, respectively, but increased the O$_3$ concentration by 51.1%. In Wuhan, the policy decreased AQI and the

| Variables          | ln (AQI)  | ln (PM$_{2.5}$) | ln (PM$_{10}$) | ln (SO$_2$)  | ln (NO$_2$) | ln (O$_3$)   |
|--------------------|-----------|----------------|---------------|--------------|-------------|--------------|
| IND × Treat        | −0.189*** | −0.295***      | −0.313***     | −0.308**     | −0.553***   | 0.511***     |
|                    | (0.025)   | (0.028)        | (0.028)       | (0.100)      | (0.033)     | (0.034)      |
| Holiday            | −0.006    | 0.126          | 0.017         | −0.412***    | 0.171***    |
|                    | (0.086)   | (0.083)        | (0.087)       | (0.128)      | (0.047)     |
| Temperature        | −0.013*** | −0.058***      | 0.006         | −0.007*      | −0.002      | 0.010***     |
|                    | (0.005)   | (0.004)        | (0.003)       | (0.003)      | (0.003)     |
| Relative humidity  | −0.006*** | 0.0002         | −0.013***     | −0.013***    | −0.001**    | −0.014***    |
|                    | (0.005)   | (0.0005)       | (0.006)       | (0.001)      | (0.0005)    | (0.001)      |
| Wind speed         | −0.139*** | −0.180***      | −0.136***     | −0.123***    | −0.237***   | 0.100***     |
|                    | (0.009)   | (0.007)        | (0.013)       | (0.009)      | (0.013)     | (0.022)      |
| Atmospheric pressure| −0.025*** | −0.044***      | −0.019***     | −0.011***    | −0.020***   | −0.006**     |
|                    | (0.003)   | (0.002)        | (0.004)       | (0.004)      | (0.002)     | (0.003)      |
| Precipitation      | −0.026*** | −0.043***      | −0.027***     | −0.008***    | −0.009***   | 0.010***     |
|                    | (0.002)   | (0.001)        | (0.002)       | (0.001)      | (0.001)     | (0.001)      |
| $R^2$              | 0.293     | 0.317          | 0.345         | 0.300        | 0.521       | 0.311        |
| Observations       | 2168      | 2168           | 2168          | 2168         | 2168        | 2168         |

IND and Treat are dummy variables set to 1 for the period after the production suspension and for belonging to treatment group (2020) in Eq. 4

*P < 0.05; **P < 0.01; ***P < 0.001
Table 6  Regression results of the difference-in-difference model for Wuhan

| Variables        | ln (AQI) | ln (PM$_{2.5}$) | ln (PM$_{10}$) | ln (SO$_2$) | ln (NO$_2$) | ln (O$_3$) |
|------------------|----------|-----------------|----------------|-------------|-------------|------------|
| IND × Treat      | −0.440***| −0.469***       | −0.668***      | −0.321***   | −1.03***    | 0.797***   |
|                  | (0.030)  | (0.041)         | (0.033)        | (0.025)     | (0.051)     | (0.052)    |
| Holiday          | 0.201*** | 0.250***        | 0.284***       | 0.051**     | −0.194**    | 0.349***   |
|                  | (0.052)  | (0.073)         | (0.057)        | (0.022)     | (0.083)     | (0.064)    |
| Temperature      | 0.002    | −0.004          | 0.016**        | 0.017***    | 0.019***    | 0.023***   |
|                  | (0.005)  | (0.006)         | (0.006)        | (0.003)     | (0.003)     | (0.005)    |
| Relative humidity| −0.007** | −0.003***       | −0.013***      | −0.018***   | 0.010***    | −0.025**   |
|                  | (0.0008) | (0.0008)        | (0.001)        | (0.001)     | (0.001)     | (0.001)    |
| Wind speed       | −0.064***| −0.082***       | −0.075***      | −0.126***   | −0.212***   | 0.056***   |
|                  | (0.016)  | (0.019)         | (0.019)        | (0.014)     | (0.017)     | (0.017)    |
| Atmospheric pressure | 0.001 | −0.0007         | −0.001         | −0.006**    | −0.002*     | −0.001     |
|                  | (0.001)  | (0.001)         | (0.003)        | (0.003)     | (0.001)     | (0.001)    |
| Precipitation    | −0.021***| −0.030***       | −0.020***      | −0.001      | −0.0016     | 0.011***   |
|                  | (0.001)  | (0.001)         | (0.001)        | (0.001)     | (0.0012)    | (0.001)    |
| $R^2$            | 0.325    | 0.289           | 0.389          | 0.404       | 0.585       | 0.466      |
| Observations     | 2424     | 2424            | 2424           | 2424        | 2424        | 2424       |

$IND$ and $Treat$ are dummy variables set to 1 for the period after the production suspension and for belonging to the treatment group (2020) in Eq. 4

* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$

Table 7  Regression results of the difference-in-difference model for Tangshan

| Variables        | ln (AQI) | ln (PM$_{2.5}$) | ln (PM$_{10}$) | ln (SO$_2$) | ln (NO$_2$) | ln (O$_3$) |
|------------------|----------|-----------------|----------------|-------------|-------------|------------|
| IND × Treat      | −0.052   | 0.023           | −0.149***      | −0.247***   | −0.297***   | 0.628***   |
|                  | (0.050)  | (0.058)         | (0.062)        | (0.082)     | (0.062)     | (0.071)    |
| Holiday          | 0.205*   | 0.250*          | 0.153          | 0.203       | −0.252      | 0.362***   |
|                  | (0.106)  | (0.123)         | (0.109)        | (0.135)     | (0.136)     | (0.095)    |
| Temperature      | −0.003   | −0.008          | 0.002          | 0.025***    | 0.010       | 0.035***   |
|                  | (0.008)  | (0.009)         | (0.009)        | (0.006)     | (0.007)     | (0.007)    |
| Relative humidity| 0.014*** | 0.021***        | 0.012***       | −0.0003     | 0.003***    | −0.010***  |
|                  | (0.0004) | (0.0006)        | (0.0003)       | (0.0008)    | (0.0005)    | (0.0005)   |
| Wind speed       | −0.084***| −0.165***       | −0.115***      | −0.282***   | −0.262***   | 0.113***   |
|                  | (0.005)  | (0.008)         | (0.005)        | (0.012)     | (0.005)     | (0.022)    |
| Atmospheric pressure | −0.019***| −0.022***    | −0.020***      | 0.007**     | −0.013***   | 0.002      |
|                  | (0.004)  | (0.005)         | (0.004)        | (0.003)     | (0.002)     | (0.002)    |
| Precipitation    | −0.039***| −0.046***       | −0.042***      | −0.012      | −0.017**    | 0.020***   |
|                  | (0.008)  | (0.010)         | (0.009)        | (0.009)     | (0.007)     | (0.002)    |
| $R^2$            | 0.409    | 0.532           | 0.360          | 0.264       | 0.560       | 0.589      |
| Observations     | 1725     | 1725            | 1725           | 1725        | 1725        | 1725       |

$IND$ and $Treat$ are dummy variables set to 1 for the period after the production suspension and for belonging to the treatment group (2020) in Eq. 4

* $P < 0.05$; ** $P < 0.01$; *** $P < 0.001$
concentrations of PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$ by 44%, 46.9%, 66.8%, 32.1%, and 103%, respectively, but increased the O$_3$ concentration by 79.7%. In Tangshan, PM$_{10}$, SO$_2$, and NO$_2$ decreased by 14.9%, 24.7%, and 29.7%, respectively, and O$_3$ increased by 62.8%. However, the policy had no significant impact on AQI and the PM$_{2.5}$ concentration. These results demonstrate that the spillover effects of the production suspension were generally positive, but differed greatly among the three cities. The production suspension decreased the pollutant concentrations most in Wuhan, especially in terms of the industrial-related pollutants (PM$_{2.5}$, PM$_{10}$, and NO$_2$). The spillover effect of this policy was smallest in Tangshan.

3.3.2 Test of the assumption of parallel trends

An important prerequisite for the effective application of DID models is that they meet the assumption of parallel trends (Liu, Dong, et al., 2021). This means that the trends for the treatment group (2020) and the control group (2019) are required to have the same trend before January 23. We added the interaction terms between the group dummy variable Treat and the date dummy variable Day$_j$, where $j$ represents the number of days before or after the policy implementation date, to verify that parallel trends existed during the 75 days before the implementation of the production suspension (Wang et al., 2021). We used the following equation:

$$\ln P_{it} = \alpha_0 + \sum_{j=-75}^{5} \alpha_j \text{Treat} \times \text{Day}_j + \theta_i X_{it} + \mu_i + \pi_t + \epsilon_{it}$$

where the coefficient $\alpha_j$ of the interaction term Treat$\times$Day$_j$ measures the difference between the treatment group and the control group on the $j$th day, and the other variables have the same meaning as in Eq. 4. If $\alpha_j$ is not significant before the implementation of the production suspension ($j < 0$), the parallel trend test is passed; otherwise, the parallel trend test is not passed. Figures 8, 9, and 10 show the results for Shanghai, Wuhan, and Tangshan, respectively. Based on the positions of the estimated coefficients and the 95% confidence interval, there appears to be no statistically significant difference between the trends for the treatment group and the control group (i.e., the 95% confidence intervals include 0) (Chen & Chi, 2021). Therefore, the assumption of parallel trends was met.

3.3.3 Robustness test

The robustness of our results was verified by reproducing similar results using another three cities that are comparable to Shanghai, Wuhan, and Tangshan, respectively. The three cities are Nanjing of Jiangsu Province, Xiangyang of Hubei Province and Shijiazhuang of Hebei Province. Nanjing and Shanghai are the core cities of the Yangtze River Delta and have alike characteristics. Xiangyang is the second-largest city in Hubei Province and is the second most severely affected city by the COVID-19 pandemic in Hubei Province, after Wuhan. Shijiazhuang is the capital of Hebei Province and the second-largest city in Hebei. Like Tangshan, Shijiazhuang also a city with large portion of continuous process industrial. Therefore, we chose Nanjing, Xiangyang, and Shijiazhuang to verify the robustness of our results. If the impact of production suspension on air quality is still significant in Nanjing, Xiangyang, and Shijiazhuang, it proves that our results are not limited to one single case, but can be generalized. The results are shown in Table 8. The spillover effects of
production suspension in Nanjing, Xiangyang, and Shijiazhuang are very similar to those in Shanghai, Wuhan, and Tangshan, respectively. It proves that our results are robust.

4 Discussion

Because COVID-19 is extremely contagious, the Chinese government implemented severe nationwide prevention and control measures, including traffic restrictions and production suspension. These policies produced different results in Shanghai, Wuhan, and Tangshan.
To investigate the causes of these differences, we explored the sources of air pollution. The main sources of air pollution in China are industrial, mobile, dust, and living sources (Liu et al., 2017; Xu & Lin, 2018; Zhang et al., 2018). Industrial sources mainly refer to industrial emissions and coal consumption, which mainly generate PM$_{2.5}$, PM$_{10}$, SO$_2$, and NO$_2$ emissions. Thermal power generation included in industrial source accounts for 20.1% of the total SO$_2$ emission and 32.6% of the total NO$_x$ emission in China (Huang et al., 2017). Therefore, PM$_{2.5}$ and SO$_2$ are often considered to be representative pollutants for industrial sources. Mobile sources mainly refer to vehicle emissions and mainly generate NO$_2$ emission. Dust sources include road dust and construction site dust and mainly generate PM$_{2.5}$ and PM$_{10}$. Living sources include biomass burning and household cooking. In Shanghai, the vast majority of industrial activities were suspended resulting in a significant reduction in pollution from industrial sources. The reduction in the number of logistics vehicles on

Fig. 9 Results of the parallel trend test for pollutants in Wuhan
the road has reduced emissions from mobile sources. Suspension of construction activities and traffic restrictions reduced dust emissions in Shanghai. In Wuhan, industrial, mobile, and dust sources were almost completely cut off, and pollution from these sources was minimized due to the lockdown measures. Tangshan is a typical industrial city, and it has many continuous process enterprises, such as steel plants. These plants were still in operation during the Level I Response period, so industrial sources were still present. Similar to the other two cities, suspension of construction activities in Tangshan reduced emissions from dust sources and traffic restrictions reduced pollution from mobile sources. Because the populations of the three cities did not change during the Level I Response period, the air pollution from living sources can be exempted from a primary cause of the diverse spillover effects because it was unlikely to change. The contribution of dust sources to air pollution is relatively low and is not sufficient to cause significant differences in spillover

**Fig. 10** Results of the parallel trend test for pollutants in Tangshan
Diverse spillover effects among the three cities. Therefore, the difference in the spillover effects among the cities can be attributed primarily to mobile sources (e.g., vehicles) and industrial sources (e.g., thermal power plants and steel plants).

### 4.1 Diverse spillover effects of traffic restrictions

At the traffic stations, the differences of the spillover effect of traffic restrictions between cities were obvious. The pollutant concentrations at the traffic stations decreased most in Wuhan, followed by Shanghai and then Tangshan. There are several reasons for this phenomenon. First, Wuhan was the city most severely affected by the COVID-19 outbreak and was the first Chinese city to adopt traffic restriction measures. Wuhan announced its closure on January 23, 2020, and closed vehicle access to Wuhan, so the traffic restriction measure was implemented earlier than in other cities, resulting in a greater improvement of air quality than in cities that implemented this control later.

Second, the traffic development level is not the same for the three cities. There are 4.43 × 10^6 vehicles in Shanghai, 3.51 × 10^6 in Wuhan, and 2.34 × 10^6 in Tangshan. According to the “Annual Report on Road Network Density and Traffic Operation in Major Chinese Cities” released in 2020, the road network density was 7.20 km/km² in Shanghai and 6.0 km/km² in Wuhan. The road network density of Tangshan can be calculated as 1.41 km/km² based on data in the “Tangshan Statistical Yearbook 2020.” Obviously, the road network is better developed in Shanghai and Wuhan than in Tangshan.

Third, the SO₂/NO₂ ratio is often used to evaluate the relative contribution of industrial and mobile sources to air pollution (Aneja et al., 2002). A higher ratio indicates that industrial sources contribute more, and mobile sources contribute less to air pollution. During the T2 period, the SO₂/NO₂ ratios in Shanghai, Wuhan, and Tangshan were 0.14, 0.18, and 0.42, respectively. The corresponding values during the T1 period were 0.20, 0.38, and 0.50, respectively. The ratio was highest in Tangshan during both periods. This demonstrates that Tangshan’s mobile sources contributed the least to air pollution both before and after the Level I Response. In contrast, Shanghai’s mobile sources contributed the most to air pollution. Traffic in Shanghai and Wuhan is more developed than in Tangshan and contributes more to air pollution in these cities. Therefore, the spillover effects of traffic restrictions were least obvious in Tangshan and most obvious in Wuhan.

### Table 8 The spillover effects of production suspension in Nanjing, Xiangyang, and Shijiazhuang

| Variables | ln (AQI) | ln (PM_{2.5}) | ln (PM_{10}) | ln (SO₂) | ln (NO₂) | ln (O₃) |
|-----------|----------|---------------|--------------|----------|----------|--------|
| Nanjing | | | | | | |
| IND×Treat | −0.342*** | −0.354*** | −0.428*** | −0.319*** | −0.666*** | 0.704*** |
| | (0.025) | (0.020) | (0.021) | (0.091) | (0.035) | (0.053) |
| Xiangyang | | | | | | |
| IND×Treat | −0.316** | −0.345** | −0.371*** | −0.021 | −0.728*** | 0.672*** |
| | (0.068) | (0.085) | (0.062) | (0.031) | (0.071) | (0.082) |
| Shijiazhuang | | | | | | |
| IND×Treat | −0.119** | −0.087 | −0.215*** | −0.053 | −0.408*** | 0.771*** |
| | (0.055) | (0.061) | (0.066) | (0.087) | (0.092) | (0.099) |

*P < 0.05; **P < 0.01; ***P < 0.001
4.2 Diverse spillover effects of industry suspension

Due to the needs of COVID-19 prevention and control, most industrial enterprises stopped operations, and only some continuous process enterprises such as steel plants, thermal power plants, and metallurgical plants continued to operate.

The values of SO$_2$/CO are widely used to analyze the contribution of coal combustion to air pollution, with higher values of SO$_2$/CO indicating a greater contribution of coal combustion to air pollution (Yang et al., 2020). Figure 11 shows the SO$_2$/CO values in Shanghai, Wuhan, and Tangshan during each period. The values in Tangshan were very high in each period and did not significantly decrease during the T2 period. We know that coal is the main energy source for these continuous process enterprises. The fact that the SO$_2$/CO values did not decrease greatly can only be attributed to the continuous operation of such enterprises during the T2 period.

We used the annual industrial SO$_2$ emission per 100 km$^2$ and the annual industrial dust emission per 100 km$^2$ to measure the scale of the continuous process industries in each city. According to the China Statistical Yearbook on Environment 2019, industrial SO$_2$ emission and industrial dust emission from the industries that were less affected by the COVID-19 response, such as steel plants and thermal power plants, account for more than 80% of the total emission in China. Therefore, the higher the annual industrial SO$_2$ emission per 100 km$^2$ and annual industrial dust emission per 100 km$^2$, the larger the scale of the continuous process industries. According to the China City Statistical Yearbook 2018, the annual industrial SO$_2$ emission per 100 km$^2$ in Shanghai, Wuhan, and Tangshan was 2.00 t, 1.64 t, and 8.89 t, respectively, and the annual industrial dust emission per 100 km$^2$ was 4.77 t, 4.94 t, and 18.29 t, respectively. Therefore, the scale of continuous process industries was largest in Tangshan, followed by Wuhan and then Shanghai. Given that these industries were not greatly affected by the production suspension policy, the difference in the scale of the continuous process industries among the three cities resulted primarily in the diverse spillover effects of production suspension on air quality.

![Fig. 11 The SO$_2$/CO ratios in the three cities during the four time periods](image)
4.3 Increased O₃ pollution during level I response period

The impact of traffic restrictions and production suspension on air quality was also reflected in the increasing O₃ concentration. A large increase of the O₃ concentration occurred at both the traffic and non-traffic stations, but the magnitudes of the changes differed greatly among the three cities. There are several possible reasons for the increased O₃ concentration at traffic stations. First, O₃ is produced by a photochemical reaction between volatile organic compounds (VOCs) and nitrogen oxides (NOₓ) (Li et al., 2019). The production of O₃ depends on the ratio of VOCs to NOₓ; a high ratio represents increased O₃ formation. With traffic restrictions implemented, a reduction in VOCs emission would reduce O₃ formation, whereas a reduction in NOₓ emission would increase O₃ formation. Zeng et al. (2018) found that the reduction ratio of the VOCs to NOₓ concentrations should not be lower than 0.73 to control O₃ pollution. During the Level I Response period, traffic restrictions decreased NOₓ emission more than it reduced VOCs emission, thereby resulting in a higher VOC/NOₓ ratio and increased O₃ production (Brancher, 2021; Campbell et al., 2021). Shanghai, Wuhan, and Tangshan had different levels of traffic development, so the different changes in the precursors of O₃ (i.e., in VOCs and NOₓ) would directly result in different increases of the O₃ concentration among three cities. Second, the products of this complex photochemical reaction are not only O₃ but also NO. The freshly produced NO and the NO that is already in the air will together deplete the O₃ (NO + O₃ → NO₂ + O₂). During the Level I Response period, traffic restrictions inevitably reduced the NO concentration at the traffic stations. The decreased NO concentration would reduce the consumption of O₃, leading to a large increase of the O₃ concentration. Different changes in the NO concentrations at the traffic stations would also contribute to the diverse increases in the O₃ concentration. Under the influence of the abovementioned factors, the O₃ concentration increased by 17.9% in Shanghai, 54.7% in Wuhan, and 9.3% in Tangshan.

There are also several possible reasons for the increase of O₃ concentrations at the non-traffic stations. Researchers found that a decrease in the PM₂.₅ concentration can also lead to an increase in the O₃ concentration (Li et al., 2017; Liu et al., 2013). Because PM₂.₅ can eliminate the precursors of O₃, including hydroxyl radicals and nitrogen–oxygen-free radicals. When the PM₂.₅ concentration falls, the concentrations of hydroxyl radicals and nitrogen–oxygen-free radicals in the air will increase, thereby promoting the production of O₃. In addition, as PM₂.₅ decreased during the Level I Response, the higher amount of solar radiation would reach the near-surface air, thereby accelerating the photochemical reactions involved in ozone production, so more O₃ would be produced (Wolff et al., 2013). Our results show that the production suspension decreased PM₂.₅ concentrations by 29.5% and 46.9% in Shanghai, Wuhan. This would have had an important impact on the changes of O₃ concentrations at the non-traffic stations.

5 Conclusions and implications

In this study, we analyzed the spillover effects of the traffic restrictions and production suspension adopted by the Chinese government to control the COVID-19 pandemic on air quality in Shanghai, Wuhan, and Tangshan. We found that the strict prevention and control measures greatly reduced AQI and the concentrations of four air pollutants (PM₂.₅, PM₁₀, SO₂, and NO₂), but the O₃ concentrations increased. Moreover, the
amplitude of the changes differed among the cities. During the Level I Response period, NO₂ decreased the most, by 30.3% in Shanghai, 51.8% in Wuhan, and 16.0% in Tangshan at all stations compared with the corresponding periods in 2019. The different amplitudes of the changes in NO₂ concentrations resulted from the difference in the traffic development level. Regarding to PM₁₀ and PM₂.₅, Shanghai decreased by 23.6% and 26.7%, respectively, and Wuhan decreased by 35.8% and 36.3%, which represents the largest decrease among the three cities. Tangshan’s PM₂.₅ and PM₁₀ decreased by 6.7% and 14.3%, respectively. These differences in the change of PM₂.₅ were mainly because of the various number of remaining pollution sources during the Level I Response period. These sources were mainly high-polluting enterprises such as thermal power plants, and the COVID-19 restrictions did not exert much impact on such enterprises.

Based on the different spillover effects, we propose some policy suggestions to promote future air pollution control. Our results demonstrate that differences in the characteristics of three types of cities led to diverse spillover effects of COVID-19 control measures. Therefore, the air pollution control measures should account for the distinctive characteristics of each city instead of choosing a "one size fits all" policy, which could be less effective and more expensive. The spillover effects of traffic restrictions and production suspension are highly correlated with the level of traffic development and the scale of the continuous process industries. High traffic development level would lead to more traffic-related emission reductions when traffic restrictions are implemented. Conversely, the large scale of the continuous process industries would lead to the smaller spillover effect of production suspension. Cities with high traffic development level have great potential to reduce their traffic-related emissions. Therefore, governments should try to reduce the mobile sources to improve the air quality through the measures of promotion of public transportation and development of new vehicles that use clean energy. While encouraging residents to use public transportation, the government should also promote vehicles that use clean energy to replace the fuel-powered vehicles in the public transportation sector. For cities with a large scale of continuous process industries, such as Tangshan, there is high potential to reduce industrial emissions. In the short term, air pollution control should focus on curbing industrial emissions, and government incentives or subsidies can be used to promote these reductions by reducing their impact on the operating costs of the affected enterprises. In the long term, the transformation and upgrading of highly polluting enterprises should be accelerated, and whole-process emission reduction approaches and technology should be vigorously promoted.

This study also found that O₃ concentrations increased significantly during the Level I Response period, 11.9% in Shanghai, 46.5% in Wuhan, and 9.8% in Tangshan. The O₃ increase is due to the imbalanced reduction of NOₓ and VOCs, leading to a higher VOCs/NOₓ ratio. Many studies have found that the higher VOC/NOₓ ratio will produce more O₃ (Peralta et al., 2021; Rathod et al., 2021; Sicard et al., 2020). As we know, ozone is a secondary pollutant. The key to controlling O₃ pollution is to reduce the precursors of O₃ including NOₓ and VOCs. Reducing the number of mobile and industrial sources are ways to control O₃ pollution. It should be noted that traffic restrictions produced more reduction of NOₓ emissions than that of VOCs emissions during the Level I Response period, resulting in a higher VOC/NOₓ ratio and then increased O₃ production. In recent years, O₃ has replaced PM₁₀ as the primary pollutant in some Chinese cities, and it is very harmful to health. Therefore, measures must be taken to control O₃ pollution. This COVID-19 pandemic provided insights into O₃ pollution control. Future O₃ pollution control strategies should consider an equilibrium between the emission reductions of NOₓ and VOCs.
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References

Aneja, V. P., Agarwal, A., Roelle, P. A., Phillips, S. B., & Yablonsky, R. (2002). Measurements and analysis of criteria pollutants in New Delhi, India. Environment International, 27(1), 35–42.

Bao, R., & Zhang, A. (2020). Does lockdown reduce air pollution? Evidence from 44 cities in northern China. Science of the Total Environment, 731, 139052.

Benchirf, A., Wheida, A., Tahiri, M., Shubbbar, R. M., & Biswas, B. (2021). Air quality during three covid-19 lockdown phases: AQI, PM$_{2.5}$ and NO$_2$ assessment in cities with more than 1 million inhabitants. Sustainable Cities and Society, 74, 103170.

Brancher, M. (2021). Increased ozone pollution alongside reduced nitrogen dioxide concentrations during Vienna’s first COVID-19 lockdown: Significance for air quality management. Environmental Pollution, 284, 117153.

Campbell, P. C., Tong, D., Tang, Y., Baker, B., Lee, P., Saylor, R., Stein, A., Ma, S., Lamsal, L., & Qu, Z. (2021). Impacts of the COVID-19 economic slowdown on ozone pollution in the US. Atmospheric Environment, 264, 118713.

Chen, S., & Chi, H. (2021). Analysis of the environmental effects of the clean heating policy in Northern China. Sustainability, 13(12), 6695.

Chen, Y., Zhang, S., Peng, C., Shi, G., & Yang, F. (2020). Impact of the COVID-19 pandemic and control measures on air quality and aerosol light absorption in southwestern China. Science of the Total Environment, 749, 141419.

Chen, Z., Hao, X., Zhang, X., & Chen, F. (2021). Have traffic restrictions improved air quality? A shock from COVID-19. Journal of Cleaner Production, 279, 123622.

Dacre, H. F., Mortimer, A. H., & Neal, L. S. (2020). How have surface NO2 concentrations changed as a result of the UK’s COVID-19 travel restrictions? Environmental Research Letters, 15(10), 104089.

Filonchyk, M., Hurynovich, V., & Yan, H. (2020). Impact of Covid-19 lockdown on air quality in the Poland, Eastern Europe. Environmental Research, 198(2), 110454.

Ghahremanloo, M., Lops, Y., Choi, Y., & Mousavinezhad, S. (2021). Impact of the COVID-19 outbreak on air pollution levels in East Asia. Science of the Total Environment, 754, 142226.

González-Pardo, J., Ceballos-Santos, S., Manzanas, R., Santibáñez, M., & Fernández-Olmo, I. (2022). Estimating changes in air pollutant levels due to COVID-19 lockdown measures based on a business-as-usual prediction scenario using data mining models: A case-study for urban traffic sites in Spain. Science of The Total Environment, 823, 153786.

Gope, S., Dawn, S., & Das, S. S. (2021). Effect of COVID-19 pandemic on air quality: A study based on Air Quality Index. Environmental Science and Pollution Research, 28, 35564–35583.

He, C., Hong, S., Zhang, L., Mu, H., Xin, A., Zhou, Y., Liu, J., Liu, N., Su, Y., Tian, Y., & Ke, B. (2021). Global, continental, and national variation in PM$_{2.5}$, O$_3$, and NO$_2$ concentrations during the early 2020 COVID-19 lockdown. Atmospheric Pollution Research, 12(3), 136–145.

Huang, L., Hu, J., Chen, M., & Zhang, H. (2017). Impacts of power generation on air quality in China—part I: An overview. Resources, Conservation and Recycling, 121, 103–114.

Ikhlasse, H., Benjamin, D., Vincent, C., & Hicham, M. (2021). Environmental impacts of pre/during and post-lockdown periods on prominent air pollutants in France. Environment, Development and Sustainability, 1–22.

Jevtic, M., Matkovic, V., Van Den Hazel, P., & Bouland, C. (2021). Environment—lockdown, air pollution and related diseases: Could we learn something and make it last? European Journal of Public Health, 31(Supplement_4), iv36–iv39.

Jiaxin, C., Hui, H., Feifei, W., Mi, Z., Ting, Z., Shicheng, Y., Ruqiao, B., Nan, C., Ke, X., & Hao, H. (2021). Air quality characteristics in Wuhan (China) during the 2020 COVID-19 pandemic. Environmental Research, 195, 110879.

Lau, J., Hung, W. T., Cheung, C. S., & Yuen, D. (2008). Contributions of roadside vehicle emissions to general air quality in Hong Kong. Transportation Research Part D: Transport and Environment, 13(1), 19–26.

Le, T., Wang, Y., Liu, L., Yang, J., Yung, Y. L., Li, G., & Seinfeld, J. H. (2020). Unexpected air pollution with marked emission reductions during the COVID-19 outbreak in China. Science, 369(6504), eabb7431.
Li, K., Jacob, D. J., Liao, H., Shen, L., Zhang, Q., & Bates, K. H. (2019). Anthropogenic drivers of 2013–2017 trends in summer surface ozone in China. Proceedings of the National Academy of Sciences, 116(2), 422–427.

Li, L., Li, Q., Huang, L., Wang, Q., Zhu, A., Xu, J., Liu, Z., Li, H., Shi, L., Li, R., Azari, M., & Chan, A. (2020). Air quality changes during the COVID-19 lockdown over the Yangtze River Delta Region: An insight into the impact of human activity pattern changes on air pollution variation. Science of the Total Environment, 732, 139282.

Li, M., Wang, T., Xie, M., Li, S., Zhuang, B., Fu, Q., Zhao, M., Wu, H., Liu, J., Saikawa, E., & Liao, K. (2021). Drivers for the poor air quality conditions in North China Plain during the COVID-19 outbreak. Atmospheric Environment, 246, 118103.

Li, M., Wang, T., Xie, M., Zhuang, B., Li, S., Han, Y., & Chen, P. (2017). Impacts of aerosol-radiation feedback on local air quality during a severe haze episode in Nanjing megacity, eastern China. Tellus Series B-Chemical & Physical Meteorology, 69(1), 1339548.

Liu, G., Dong, X., Kong, Z., & Dong, K. (2021). Does national air quality monitoring reduce local air pollution? The case of pm2.5 for china. Journal of Environmental Management, 296(4), 113232.

Liu, H., Wang, X. M., Pang, J. M., & He, K. B. (2013). Feasibility and difficulties of China’s new air quality standard compliance: PRD case of PM2.5 and ozone from 2010 to 2025. Atmospheric Chemistry and Physics, 13(23), 12013–12027.

Liu, Q., Harris, J. T., Long, S. C., Sun, D., & Yang, C. (2020). Spatiotemporal impacts of COVID-19 on air pollution in California, USA. Science of the Total Environment, 750, 141592.

Liu, Y. H., Liao, W. Y., Li, F. S., Huang, Y. T., & Xu, W. J. (2017). Vehicle emission trends in China’s Guangdong Province from 1994 to 2014. Science of the Total Environment, 586, 512–521.

Liu, Y., Wang, T., Stavrakou, T., Elguindi, N., Dounmba, T., Granier, C., Bouarar, I., Gaubert, B., & Brasseur, G. P. (2021). Diverse response of surface ozone to COVID-19 lockdown in China. Science of the Total Environment, 789, 147739.

Ming, W., Zhou, Z., Ai, H., Bi, H., & Zhong, Y. (2020). COVID-19 and air quality: Evidence from China. Emerging Markets Finance and Trade, 56(10), 2422–2442.

Mo, Z., Huang, J., Chen, Z., Zhou, B., Zhu, K., Liu, H., Mu, Y., Zhang, D., & Wang, S. (2021). Cause analysis of PM2.5 pollution during the COVID-19 lockdown in Nanning, China. Scientific Reports, 11(1), 11119.

Mousazadeh, M., Paizal, B., Nghiadli, Z., Mortezazania, Z., Hashemi, M., Karamati Niaragh, E., Aghababaei, M., Ghorbankhani, M., Lichtfouse, E., Sillanpää, M., & Hashim, K. S. (2021). Positive environmental effects of the coronavirus 2020 episode: a review. Environment, Development and Sustainability, 23(9), 12738–12760.

Oo, T. K., Arunrat, N., Kongsrurakan, P., Sereenonchai, S., & Wang, C. (2021). Nitrogen dioxide (NO2) level changes during the control of COVID-19 pandemic in Thailand. Aerosol and Air Quality Research, 21(6), 200440.

Pal, S. C., Chowdhuri, I., Saha, A., Chakrabortty, R., Roy, P., Ghosh, M., & Shit, M. (2021). Improvement in ambient-air-quality reduced temperature during the COVID-19 lockdown period in India. Environment, Development and Sustainability, 23(6), 9581–9608.

Pei, Z. P., Han, G., Ma, X., & Gong, W. (2020). Response of major air pollutants to COVID-19 lockdowns in China. Science of the Total Environment, 743, 140879.

Peralta, O., Ortiz-Álvarez, A., Torres-Jardón, R., Suárez-Lastra, M., Castro, T., & Ruíz-Suárez, L. G. (2021). Ozone over Mexico City during the COVID−19 pandemic. Science of the Total Environment, 761, 143183.

Rathod, A., Sahi, S. K., Singh, S., & Beig, G. (2021). Anomalous behaviour of ozone under COVID-19 and explicit diagnosis of O3-NOx-VOCs mechanism. Heliyon, 7(2), e06142.

Rodriguez-Urrego, D., & Rodríguez-Urrego, L. (2020). Air quality during the COVID-19: PM2.5 analysis in the 50 most polluted capital cities in the world. Environmental Pollution, 266, 115042.

Sicard, P., De Marco, A., Agathokleous, E., Feng, Z., Xu, X., Paolelli, E., Rodriguez, J. J. D., & Calatayud, V. (2020). Amplified ozone pollution in cities during the COVID-19 lockdown. Science of the Total Environment, 735, 135942.

Sohrabi, C., Alsafi, Z., O’Neill, N., Khan, M., & Agha, R. (2020). World Health Organization declares global emergency: A review of the 2019 novel coronavirus (COVID-19). International Journal of Surgery, 76, 71–76.

Solberg, S., Walker, S. E., Schneider, P., & Guerreiro, C. (2021). Quantifying the impact of the Covid-19 lockdown measures on nitrogen dioxide levels throughout Europe. Atmosphere, 12(2), 131.

Sulaymon, D. I., Hopke, P. K., Yang, Z., Mei, X., & Hua, J. (2021). COVID-19 pandemic in Wuhan: Ambient air quality and the relationships between criteria air pollutants and meteorological variables before, during, and after lockdown. Atmospheric Research, 250, 105362.
Tang, X., Yang, B., & Wu, Z. (2021). How covid-19 impacted pm 2.5 and air quality in china’s main cities. *IOP Conference Series: Earth and Environmental Science, 621*(1), 012118.

Tobías, A., Carnerero, C., Reche, C., Massagué, J., Via, M., Mingüillón, M. C., Alastuey, A., & Querol, X. (2020). Changes in air quality during the lockdown in Barcelona (Spain) one month into the SARS-CoV-2 epidemic. *Science of the Total Environment, 726*, 138540.

Wan, Z., Zhou, X., Zhang, Q., & Chen, J. (2019). Do ship emission control areas in China reduce sulfur dioxide concentrations in local air? A study on causal effect using the difference-in-difference model. *Marine Pollution Bulletin, 149*, 110506.

Wang, J., Xu, X., Wang, S., He, S., & He, P. (2021). Heterogeneous effects of COVID-19 lockdown measures on air quality in Northern China. *Applied Energy, 282*, 116179.

Wang, P., Chen, K., Zhu, S., Wang, P., & Zhang, H. (2020a). Severe air pollution events not avoided by reduced anthropogenic activities during COVID-19 outbreak. *Resources, Conservation and Recycling, 158*, 104814.

Wang, Y., Yuan, Y., Wang, Q., Liu, C., Zhi, Q., & Cao, J. (2020b). Changes in air quality related to the control of coronavirus in China: Implications for traffic and industrial emissions. *Science of the Total Environment, 731*, 139133.

Wang, Z., Li, X., Wang, Z., Wu, X., Che, F., & Nie, P. (2013). Application status of Models-3/CMAQ in environmental management. *Environmental Science and Technology, 36*, 386–391.

Wolff, G. T., Kahlbaum, D. F., & Heuss, J. M. (2013). The vanishing ozone weekday/weekend effect. *Journal of the Air & Waste Management Association, 63*(3), 292–299.

Xin, Y., Shao, S., Wang, Z., Xu, Z., & Li, H. (2021). COVID-2019 lockdown in Beijing: A rare opportunity to analyze the contribution rate of road traffic to air pollutants. *Sustainable Cities and Society, 75*, 102989.

Xu, B., & Lin, B. (2018). What cause large regional differences in PM2.5 pollutions in China? Evidence from quantile regression model. *Journal of Cleaner Production, 174*, 447–461.

Yang, Y., Zhao, L., Xie, Y., Wang, C., & Xue, J. (2020). China’s COVID-19 lockdown challenges the ultralow emission policy. *Atmospheric Pollution Research, 12*(2), 395–403.

Zeng, P., Lyu, X. P., Guo, H., Cheng, H. R., Jiang, F., Pan, W. Z., Wang, Z. W., Liang, S. W., & Hu, Y. Q. (2018). Causes of ozone pollution in summer in Wuhan, Central China. *Environmental Pollution, 241*, 852–861.

Zhang, T., & Tang, M. (2021). The impact of the COVID-19 pandemic on ambient air quality in China: A quasi-difference-in-difference approach. *International Journal of Environmental Research and Public Health, 18*(7), 3404.

Zhang, Y. Y., Lang, J. L., Cheng, S. Y., Li, S. Y., Zhou, Y., Zhang, H. Y., & Wang, H. Y. (2018). Chemical composition and sources of PM$_1$ and PM$_{2.5}$ in Beijing in autumn. *Science of the Total Environment, 630*, 72–82.

Zhou, M., Huang, Y., & Li, G. (2021). Changes in the concentration of air pollutants before and after the COVID-19 blockade period and their correlation with vegetation coverage. *Environmental Science and Pollution Research, 28*, 23405–23419.

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