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Green recovery or pollution rebound? Evidence from air pollution of China in the post-COVID-19 era

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A B S T R A C T
Under the strict control measures, China has achieved phased victory in combating with the COVID-19, production activities have gradually returned to normal. This paper examined whether air pollution was rebounded or realized green recovery in the post-COVID-19 era with a dataset of weather normalized pollutant concentrations using difference-in-differences models. Results showed that air pollution experienced a significant decline due to the wide range of control measures. With entering the post-epidemic period, air pollution raised due to the orderly production resumption. Specifically, production resumption increased the PM2.5 concentrations of lockdown cities and non-lockdown cities by 43.2% (22.3 μg/m3) and 35.9% (17.3 μg/m3) compared with that in the period of COVID-19 breakout. Although the economic activities of China have been gradually recovered, PM2.5 concentrations were 8.8–11.2 μg/m3 lower than the level of pre-epidemic period. In addition, the environmental effects varied across cities. With the process of production resumption, the PM2.5 concentrations of cities with higher GDP, higher secondary industry output, more private cars and higher export volume rebounded less. Most developed cities realized green recovery by economy growth and air quality improvement, such as Beijing and Shanghai. While cities with heavy industry reflected pollution rebound with slow economy recovery, such as Shenyang and Harbin. Understanding the environmental effects of control measure and production resumption can provide crucial information for developing epidemic recovery policies and dealing with pollution issues for both China and other countries.

1. Introduction

Coronavirus disease 2019 (COVID-19) has swept the globe and triggered global health crisis (Wang et al., 2020) and tremendous economic shock (Gius et al., 2021) since December 2019. As the first country to fight against the epidemic, China has taken a series of dramatic measures to prevent the epidemic spread, such as city lockdowns, closed public places, and cancelled public gatherings (Kraemer et al., 2020). After a period of strict prevention and control, China has achieved phased victory in combating with the COVID-19 (State Council of China, 2020). Chinese cities have successively cancelled lockdown and loosened control measures, and production has gradually returned to normal since March 2020 (Wang and Zhang, 2021).

Under a sequence of control measures for epidemic spread, the shutdown of non-essential industries and restrictions on traffic have greatly reduced energy consumption, followed by the temporary improvement of air quality (Cole et al., 2020; He et al., 2020). With the process of production resumption, the growth of energy consumption would inevitably stimulate air pollution. However, it is still unknown whether air pollution was rebounded or decreased compared with the normal level before the epidemic. If pollution is reduced, it is unclear whether the decline is due to the economic activity that has not returned to normal levels or to a green recovery. In this paper, we define green recovery as the economic growth with the reduction of air pollutants during the production resumption period. After all, the epidemic has altered economic activities, travel and life behavior. For example, more employees prefer to work from home, online meetings and study even during the post-COVID-19 period. Moreover, the reduction of energy...
consumption is an opportunity for China to realize energy structure adjustment and sustainable development. If we can face the challenge and seize the opportunity, it is possible to achieve the win-win situation of epidemic control and green development.

The objectives of this study are to (i) identify the change characteristics of air quality caused by COVID-19 and production resumption in post epidemic era; (ii) quantitatively estimate the causal effects of control measures for the epidemic and production resumption on air quality; (iii) examine the heterogeneous impacts on air quality across cities and explore which cities achieved green recovery or pollution rebound. Exploring the air quality trends and their influential factors of China in the post-COVID-19 era can provide crucial information for developing epidemic recovery policies and dealing with environmental pollution issues. Specifically, China has recovered rapidly from the epidemic in the world, evaluation of the environmental effects of production resumption in China can also shed light for other countries struggling with the epidemic.

Most of the previous studies have carried out that air quality improved significantly in many countries around the world caused by the control measures for the COVID-19 in the world wide, although the impacts vary across countries. Air pollution concentrations are much lower in countries with strict lockdown measures than in those without (Cooper et al., 2022). The largest mitigation occurred in China. Specially, the PM$_{2.5}$ concentrations of lockdown cities in China decreased significantly compared with non-lockdown cities (Fan et al., 2020; He et al., 2020). Air quality index (AQI) and the concentrations of NO$_2$, PM$_{10}$ and PM$_{2.5}$ also dropped significantly by 15–38% in Northern China (Wang et al., 2021), and NO$_2$ concentrations decreased by 24 μg/m$^3$ in Wuhan (Cole et al., 2020). For the United States, the safer-at-home orders reduced PM$_{2.5}$ emissions by 25% across counties (Brodeur et al., 2021), which is contributed from the decline in vehicle travel and electricity usage (Cicala et al., 2020). Los Angeles, one of the most polluted cities in the United States, suffered 17.5% decline in PM concentrations due to the strictest lockdown measures, especially contributed from the traffic reduction (Yang et al., 2021). With the weakening of control measures, the reduction of pollutants also becomes smaller. The stay-at-home orders dropped PM$_{2.5}$ concentrations by 15% in southern California (Jiang et al., 2021). For Europe, the lockdown measures for COVID-19 control have temporarily bolstered the downward trends of air pollution in the past two decades (Geddes et al., 2016), which is caused by the less economic activity, closure of high power plants and traffic restrictions (Grange et al., 2021; Filonchyk et al., 2021). Previous studies also analyzed the impacts of different measures on air quality and found that the social distancing measures reduced the air pollution mostly due to the restrictions on traffic (Anugerah et al., 2021; Ju et al., 2021). For example, the biggest reduction of air pollutants in Israel and Indonesia was observed in NO$_x$ emissions due to the sharply decline in transportation (Agami and Dayan, 2021; Anugerah et al., 2021).

In general, a sequence of control measures for COVID-19 have brought about the significant improvements of air quality and health benefits, which were contributed by the temporary reduction of residual benefits, traffic and industrial activities (Perera et al., 2021). However, these temporary measures would not cause the long-term decline in the air quality as they have little influence on the fossil fuel-based energy structure (Le Quéré et al., 2021).

With the gradual control of the epidemic and production resumption, global CO$_2$ emissions induced by economic activities have shown a slow increasing trend since May 2020 compared with the period from January to April 2020 (Le Quéré et al., 2021). However, it is still unclear whether the air pollution will exceed that during the pre-epidemic period, as most countries are still struggling with the epidemic, taking control measures, their economy has not yet recovery. In 2020, China was the only major economy to achieve economic growth, which has experienced a 6.8% decline in GDP in the first quarter and a 3.2% growth of GDP in the second quarter (National Bureau of Statistics, 2021a,b). Therefore, it is worth studying how the air quality changes with the process of production resumption in the post-COVID-19 era.

In this study, we estimated how the control measures for the epidemic and production resumption in the post-COVID-19 era affect air quality with the following three steps. In the first step, we constructed a dataset of weather normalized pollutant concentrations with decision-tree-based random forest model. Removing the influence of weather conditions from the pollutant concentration observations can make the pollution data of different cities during different periods more comparable and identify the temporal and spatial dynamic characteristics of air pollutant concentrations in different stages of the epidemic which is one of the contributions of this paper. Based on the deweathered air pollution data, two sets of difference-in-differences (DDD) models were employed to quantify the impact of production resumption in the post-COVID-19 era. In the second step, (a) we estimated the impact of control measures on air pollution by comparing the pollutants during the period after the epidemic outbreak in 2020 and the same period in 2019 without epidemic. This effect reflected the change of air pollutants caused by production reduction and activities restriction due to the epidemic. In addition, (b) we assessed the impact of production resumption on air pollution by comparing the pollutants during epidemic outbreak period and post-COVID-19 period. In the last step, we compared the effects of estimation (a) and (b) and then obtained whether the air pollution rebounded or remained at a low level compared with that during the period without the epidemic. In order to identify the dynamic change of air pollutants in different stages of the epidemic and detect its influencing mechanism, we carried out two sets of DDD estimation and the comparison.

Our empirical findings indicated that air pollution experienced a significant decline due to the wide range of control measures caused by COVID-19. With entering the post-epidemic period, air pollution raised due to the orderly production resumption, but it still did not reach the pollution level of pre-epidemic period. Specifically, the control measures for the epidemic dropped the PM$_{2.5}$ concentrations of lockdown cities and non-lockdown cities by 78.6% (44.5 μg/m$^3$) and 46.7% (26.1 μg/m$^3$) compared with the same period in 2019, respectively. With the recovery of economic activities, production resumption brought a growth of PM$_{2.5}$ concentrations of lockdown cities and non-lockdown cities by 43.2% (22.3 μg/m$^3$) and 35.9% (17.3 μg/m$^3$) compared with the era of COVID-19 breakout. Although the economic activities of China have been gradually recovered, the pollutant level of PM$_{2.5}$ concentrations was 8.8–11.2 μg/m$^3$ lower than that in the period without epidemic. In addition, the environmental effects varied across cities. The impacts of control measure on air pollution reduction are greater in cities with higher GDP, higher secondary industry output, more private cars and higher export volume, as the energy consumption, especially the fuel energy consumption, is higher in these cities. In the period of production resumption, the pollution concentrations of these cities rebound less. Some cities with heavy industry as the main industry recovered more slowly in post-epidemic era, such as Shenyang in Liaoning Province. While cities that seize the opportunity to promote industrial transformation and green economic stimulate have achieved green recovery in the post-epidemic era, such as Beijing. Finally, we also found the concentrations of SO$_2$ and NO$_2$ show rebound trends with the process of production resumption which were mainly contributed by the power sector and transportation sector.

2. Empirical strategy
2.1. Weather normalization of air pollution data

Original dataset of AQI and the concentrations of six air pollutants (PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_x$, CO, O$_3$) are from China National Environmental Monitoring Centre, which provides the hourly pollution concentrations of 1605 monitoring stations (China National Environmental Monitoring Centre, 2021). To gain city-level data, we aggregate station-level data
using the inverse distance weights (He et al., 2020). The daily pollutant data of prefecture level cities is obtained by calculating the average value of hourly data. Meteorological data at station-level includes average temperature, maximum wind speed, wind direction, precipitation, relative humidity and air pressure, which is collected from the “worldmet” R package (Carslaw, 2017; NOAA, 2016). By distribution the location of the stations, we get the meteorological data of 200 prefecture-level cities. Finally, we match them with air pollution data and gain the dataset of 200 prefecture-level cities from January 1st 2019 to October 31st 2020. The geographical distribution of the sample cities is shown in Fig. S1.

This paper uses three steps to achieve the assessment of the environmental impact of production resumption in the post-COVID-19 era. The first step is to construct a dataset of weather normalized pollutant concentrations with decision-tree-based random forest model. Air pollution concentrations are partially affected by weather conditions, such as wind speed, temperature, humidity, and precipitation (Fu and Gu, 2017), which make it difficult to accurately identify the impact of policy on air pollutant concentrations (Carslaw and Carslaw, 2019). Hence, the best way to clearly identify the policy effect is to remove the influence of weather conditions from the pollutant concentration observations (Cole et al., 2020; Wise and Comrie, 2005). Stripping out the weather factors can make the pollutant concentration data of different cities during different periods more comparable and make the control group and treatment group as similar as possible before the policy intervention in the following regression models.

Random forest algorithm based machine learning techniques is widely used for meteorological normalization, as it allows for a more flexible relationship compared with simple linear model and measures the importance of variables and predictor choices (Grange et al., 2018; Varian, 2014). They predicted different pollutants concentrations at a certain time with a re-sampled predictor dataset. This paper employs the weather normalized procedure of Vu et al. (2019) and applies ‘rmweather’ R packages developed by Grange et al. (2018). We remove the weather factors from pollutant concentrations and retained the seasonal variations which make it possible to compare the air pollution condition during same periods in different years. AQI and six air pollutant concentrations for each city are used as dependent variables, and the meteorological variables (average temperature, wind direction, wind speed, relative humidity and atmospheric pressure) and time variables (year, month, weekday) are used as predictor variables to construct a decision-tree-based random forest model. The whole dataset was randomly distributed into a training set (80%) and a test set (20%). We use the training set to train the random forest model, and use the test set to test the model robustness. Table S1 presents the summary statistics of weather normalized pollutants data and meteorological variables.

### 2.2. Empirical methods

Based on the deweathered air pollution data, this paper evaluated the impacts of control measures for the epidemic and production resumption in the post-COVID-19 era on air pollution. We can accurately identify whether the changes of pollutants rebounded or remained green during the post-COVID-19 period through examining the impact of control measures, such as industrial shutdown, travel restriction and social distance. Hence, we constructed two sets of DID models for estimation.

First, we assessed the effect of COVID-19 control measures on air quality. Our main model (1) is DID model with city and time fixed effects, as follows:

\[
\text{Pollutant}_i = \beta_0 + \beta_1 \text{Trt}_{\text{Covid}} \times \text{Post}_{\text{Covid}} + \beta_2 X_{ij} + \mu_i + \tau_j + \epsilon_{ij}
\]  

(1)

where \text{Pollutant}_i is the dependent variable associated with city \text{\textit{i}}’s air pollution on date \text{\textit{j}}. We use seven dependent variables in our analysis: deweathered AQI, deweathered concentrations of PM$_{2.5}$, PM$_{10}$, SO$_2$, NO$_2$, CO and O$_3$. We select the period from January 1st to February 28th in 2019 and in 2020 as research period, as the epidemic control measures were fully implemented from January 23rd to February 28th in 2020, while after February 28, some cities gradually cancelled lockdown and resumed work. Samples in 2019 are regarded as the control group as no cities were affected by the epidemic, and samples in 2020 are the treatment group in the model. \text{Trt}_{\text{Covid}} is a dummy variable and takes the value 1 if it belongs to the treatment group and 0 if it belongs to the control group. The independent dummy variable \text{Post}_{\text{Covid}} indicates whether date \text{\textit{j}} is after the breakout of COVID-19 (January 23rd), \beta_1 is the coefficient of the interaction term, which measures the changes of air pollutants caused by the epidemic control measures compared with the same period in 2019. We collected \text{X}_{ij} as the control variable, which included daily temperature, humidity, wind speed, and a binary indicator for public holidays. We further include fixed effects in this model, where \tau_j reflects the time fixed effects including date fixed effects and year fixed effects, \mu_i reflects the city fixed effects that flexibly control for city heterogeneity. \epsilon_{ij} is the random error term.

Furthermore, we use two different groups of samples: the lockdown cities and non-lockdown cities, to identify the impact of lockdown on air pollution. As 93 Chinese cities have locked down faced with break of COVID-19, the measures include not only production shutdown, but also restricting travel and social intercourse (He et al., 2020). The list of lockdown cities and non-lockdown cities are shown in Table S2. We examined that whether these more stringent and deeper closures would have different impacts on production resumption.

Second, we estimated the impact of production resumption on air pollution by comparing the pollutants of epidemic outbreak period and the production consumption period. DID model (2) with city and time fixed effects is used as follows:

\[
\text{Pollutant}_i = \beta_0 + \beta_1 \text{Post}_{\text{resumption}} \times \text{Trt}_{\text{resumption}} + \beta_2 X_{ij} + \mu_i + \tau_j + \epsilon_{ij}
\]  

(2)

where dependent variable \text{\textit{Pollutant}} is control variable \text{\textit{X}_{ij}}, and the variables indicate fixed effects and are the same as that in model (1). \text{Trt}_{\text{resumption}} is a dummy variable and takes the value 1 if it is in the treatment group and 0 if it belongs to the control group. We used the sample in 2019 as the control group and the sample in 2020 as the treatment group. The independent dummy variable \text{Post}_{\text{resumption}} indicates whether date \text{\textit{j}} is after the resumption (April). \beta_1 is the coefficient of the interaction term, which measures the changes of air pollutants from epidemic outbreak to production resumption compared with the same period in 2019. Similar with the sample of model (1), we also use two different groups of samples: the lockdown cities and non-lockdown cities, to identify the impact of production resumption on air pollution.

A parallel trend between the control group and treatment group is a basic assumption for DID model. We evaluated the effect of control measures in each week before and after the policy and verified the parallel trend assumption (see Fig. S2-a). Similarly, we evaluated the effect of production resumption in one month before and six months after the policy and verified the parallel trend assumption (see Fig. S2-b).

We selected the period from January 23rd to February 28th and April 1st to October 31st in 2019 and in 2020 as research period for the two sets of DID model, respectively. COVID-19 was broken out on January 23rd 2021 and control measures were implemented until February 28th. After that, cities resumed work and production gradually. As the process of production resumption was advancing step by step in March, samples in March are not included in model (2). All provinces asked students to return to school from April 7th to April 27th in 2020. The resumption time refers to the opening time of junior grade three and senior grade three in different provinces. In general, the resumption time...
would be 28 days after the local newly epidemic cases were cleared. Hence, returning to school represents the recovery of production and normal life, this paper uses the time of returning to school proposed by each province as the start time of production resumption. Table S3 presents the schedule of returning to school.

### 3. Results

#### 3.1. Changes in deweathered air pollution data

Deweathered air pollution data presents a clearer pattern and makes the comparison of data in different years more credible. Fig. 1 presents a plot of air pollution concentrations at daily level to show the overall trends in the observed data and deweathered data for PM$_{2.5}$ ($\mu$g/m$^3$), SO$_2$ ($\mu$g/m$^3$), and NO$_2$($\mu$g/m$^3$) respectively between January 2018 to October 2020. Both groups of data reflect a general downward trend and seasonal characteristics over time. We can also see from Fig. 1 that the weather normalization processes make the air pollution data much smoother and allow us to quantitatively compare the changes in the air pollution. We use the deweathered data for the following analysis.

Fig. 2 presents the changes in deweathered AQI and air pollutant concentrations during the epidemic outbreak period (Period I) and post-COVID-19 period (Period II) in 2019 and 2020. Before the outbreak of COVID-19 on January 23rd, the AQI and PM$_{2.5}$ concentrations in 2020 were similar with that in 2019, which also may confirm the parallel trend hypothesis of DID estimation. The epidemic outbreak in 2020 coincided with the Spring Festival (SF) holiday in China. During the 7-day SF holiday in 2019, the pollutants first showed a short-term decline, then returned to the pre-festival level with the end of holiday. However, the changes in the air pollutants post-SF in 2020 showed a different trend. With the outbreak of COVID-19 (one day after the SF) in 2020, AQI, PM$_{2.5}$, and other five air pollutant concentrations showed sharply and continuous decline with the adoption of lockdown and other control measures until the end of February. Period II reflects the change of pollutants from epidemic situation to the process of production resumption. Before April the pollutants level in 2020 was lower than that in the same period of 2019. However, with the process of production resumption in cities, the difference of pollutants between 2019 and 2020 gradually decreased, and even the AQI, PM$_{2.5}$, PM$_{10}$, SO$_2$ and NO$_2$ in October exceeded that in the same period of 2019.

The above analysis is based on the intuitive analysis of deweathered air pollution data. It is of vital importance for quantitatively evaluating the effects of the control measures and production resumption on air pollution so that to put forward suggestions on green development and cope with the epidemic in the post-COVID-19 era.

#### 3.2. Impacts of production resumption on air pollution

To identify the impacts of production resumption, we make two steps of evaluation. In the first step, we assess the effects of epidemic control measures caused by comparing pollutants pre and post COVID-19 with model (1). Table 1 shows the impacts of COVID-19 on PM$_{2.5}$ concentrations of non-lockdown cities and lockdown cities, respectively. Results in column (1) and (3) indicate that affected by epidemic, PM$_{2.5}$ concentrations of non-lockdown cities dropped by 46.7% (26.1 $\mu$g/m$^3$) compared with the same period in 2019. For non-lockdown cities, although residents were not forced to limit travel and gathering, tourism and social activities has also been reduced and the industries were closed in varying degrees due to the impact of the epidemic and the extension of the Spring Festival.

The impacts of control measure caused by COVID-19 on air pollutants of lockdown cities are shown in column (2) and (4) of Table 1. Results present that the control measures including both city lockdown and industrial shutdown mitigated PM$_{2.5}$ concentrations by 78.6% (44.5 $\mu$g/m$^3$) and 46.7% (26.1 $\mu$g/m$^3$) in lockdown cities and non-lockdown cities, respectively. We find that the difference of the interaction term coefficients between two groups is significant by permutation test. Lockdown measures, such as travelling restrictions, commuting reduction and social activities prohibition, lead to a further sharp drop in air pollution. It proves that the contribution of traffic emissions to urban pollution is at least as high as 32%. Other study also proved that transport emission is the largest share of the decline of carbon emissions (Le Quéré et al., 2021). Apart from PM$_{2.5}$, the control measures for the epidemic also significantly dropped AQI and the concentrations of PM$_{10}$, SO$_2$, NO$_2$ and CO compared with the same period in 2019, the results are shown in Table S4.

As shown in Fig. 2, we also find that the concentrations of PM$_{10}$, SO$_2$, NO$_2$, and CO decreased significantly by 25.7–44.7% due to control measures for epidemic. While the concentration of ozone increased significantly by 12.5%, probably because the decline of nitric oxide, which reduces the reaction with ozone and raises the concentration of ozone (Seinfeld and Pandis, 1998; Sillman, 1999).

In the second step, we estimate the effects of production resumption on air pollution in post-COVID-19 era with model (2). Samples are also divided into non-lockdown cities group and lockdown cities group for estimation. Estimation results are shown in Table 2. For non-lockdown cities, production resumption brought a growth of PM$_{2.5}$ by 35.9% (17.3 $\mu$g/m$^3$) compared with the era of COVID-19 breakout. For

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**Fig. 1.** Daily averages of observed and deweathered air pollutant concentrations between January 2018 and October 2020.
lockdown cities, the concentration of PM$_{2.5}$ also increased by 43.2% (22.3 $\mu g/m^3$) compared with the pollutant under the closure measures during the epidemic period. The difference of the impacts between two groups is significant. Apart from PM$_{2.5}$, daily AQI and the concentrations of PM$_{10}$, SO$_2$, NO$_2$ and CO have increased significantly contributed by production resumption compared with the same period in 2019, the results are shown in Table S5.

Overall, pollutants experienced a significant decline due to the wide range of control measures caused by COVID-19. With entering the post-epidemic period, air pollution raised due to the orderly resumption of work and production, but it still did not reach the pollution level of pre-epidemic period. For non-lockdown cities, PM$_{2.5}$ concentrations in the period of production resumption was 8.8 $\mu g/m^3$ lower than that in no epidemic period. For lockdown cities, the value was up to 11.2 $\mu g/m^3$. As shown in Fig. 3, the changes of AQI, PM$_{10}$ and CO concentrations also present similar characteristics with that of PM$_{2.5}$. The average AQI of production resumption period were 14.8–11.4 lower than that in no epidemic period. Our results indicate that although the production and life of China has been gradually recovered after the epidemic, the pollutant level is lower than that in the period without epidemic. In other words, production and its environmental impacts in China enter into the recovery stage. But it is unclear whether the lower pollution level is due to the recovering production or the green transformation and development.

Besides, we find that the concentrations of SO$_2$ and NO$_2$ show rebound trends with the process of production resumption. The concentration of SO$_2$ and NO$_2$ were 0.6–1.3 $\mu g/m^3$, 2.4–5 $\mu g/m^3$ higher than that of no epidemic period, respectively. The main pollutant sources for SO$_2$ emission are industrial sector (63%), power sector (26%) and residential sector (10%). For NO$_2$ emissions, they are industrial sector (40%), transportation (30%) and power sector (25%) (Bo et al., 2018). As industry is the main source of PM$_{2.5}$ (60%) and PM$_{2.5}$ concentrations is down, the rebound of SO$_2$ may be caused by the emission of power sector and transportation sector.

The environmental impacts of epidemic control measures and production resumption were different between lockdown cities and other cities. On one side, the pollutants in lockdown cities dropped by 20–28% more than those in non-lockdown cities during the COVID-19 breakout period, because the former not only restricted the internal transportation and social distance, but also suspended production on a larger scale. On the other side, with the process of production resumption, the
pollution level (except for NO\textsubscript{2} and SO\textsubscript{2}) of the lockdown cities and non-lockdown cities returned to 60–66\% of the previous level, although the value of the lockdown cities was lower. It may be that the epidemic situation is more serious and the recovery is slower in lockdown cities, or other green development measures have been taken.

### 3.3. Heterogeneity across cities

COVID-19 spread throughout the country, but the number of infected people, the intensity and scope of prevention and control measures are various among cities, so the impacts of the epidemic on air pollution of different cities are also different. We investigate the change of air pollution in each city in the same period of each month.

Fig. 4 presents the temporal and spatial characteristics of pollutant concentrations changes in China. From the perspective of temporal characteristic, PM\textsubscript{2.5} concentrations decreased the most in February and March, and the number of cities with the most decline is the largest. Since April, production activities have gradually returned to normal levels, and air pollutants in some cities has even exceeded the level of the same period. In October, the number of cities with growth of pollutants increased. From the perspective of spatial characteristic, the epidemic broke out in Wuhan, Hubei Province, and then spread to the whole country. In the early February, PM\textsubscript{2.5} concentrations in central China (Hubei province located in) decreased by more than 40\%. In March 2020, the decline gradually spread across the country. Since April, air pollutants in southern and northeastern China have gradually recovered, exceeding those in the same period. From May to October, pollutants continued to drop in southern China.

Moreover, we also estimate whether the impacts of production resumption varied across different types of cities. There are no causal interpretations for heterogeneity analysis, but it helps us to identify the channels through which production resumption of COVID-19 affects air pollution. Fig. 5 presents the impact heterogeneity with consideration of GDP, industrial structure, transportation and tourism sector and export. Results show that the effects of control measure on air pollution reduction were greater in cities with higher GDP, higher secondary industry output, more private cars and higher export volume, as the energy consumption, especially the fuel energy consumption, is higher in these cities. The outbreak of the epidemic and the control measures make the economy, production activities and transportation of these cities more serious and the recovery is slower in lockdown cities, or other green development measures have been taken.

### Table 2

|                  | Non-lockdown cities | Lockdown cities | Non-lockdown cities | Lockdown cities |
|------------------|---------------------|----------------|---------------------|----------------|
|                   | (1)                 | (2)            | (1)                 | (2)            |
| \(\text{Trt}_{\text{resumption}} \times \text{Post}_{\text{resumption}}\) | 0.359***           | 0.432***       | 17.322***          | 22.321***      |
|                   | (10.39)             | (8.15)         | (10.49)             | (7.76)         |
| \(\text{Trt}_{\text{resumption}}\) | -0.406***           | -0.450***      | -20.179***          | -23.593***     |
|                   | (-12.04)            | (-8.39)        | (-11.36)            | (-7.46)        |
| \(\text{Post}_{\text{resumption}}\) | -0.383***           | -0.394***      | -18.280***          | -19.934***     |
|                   | (-14.76)            | (-9.65)        | (-12.92)            | (-7.72)        |
| City fixed effects | Yes                 | Yes            | Yes                 | Yes            |
| Date fixed effects | Yes                 | Yes            | Yes                 | Yes            |
| Year fixed effects | Yes                 | Yes            | Yes                 | Yes            |
| \(N\)              | 98,894              | 31,626         | 98,894              | 31,626         |
| \(R^2\)             | 0.6937              | 0.6837         | 0.5978              | 0.5932         |
| Empirical \(p\)-value | 0.021***           |                | 0.037**             |                |

Note: Standard errors are clustered at city level. t-test values are in parentheses. ***\(p < 0.01\); **\(p < 0.05\); *\(p < 0.1\). We use empirical \(p\)-values to test the significance of the difference of the coefficients of the interaction terms between non-lockdown cities and lockdown cities by permutation test.
cities suffer a huge impact, and the energy consumption is greatly reduced. Besides, under the global impact of the epidemic, the pollutants in regions with higher export volume decreased much more.

The effect of production resumption also varied across different types of cities. The pollution concentration in cities with higher GDP, higher secondary industry output, more private cars and higher export volume rebound less. There may be two main reasons. On one side, some cities recover more slowly in post-epidemic era, because the epidemic has a greater impact on them. On the other side, some cities have achieved economic growth and green recovery in the post-epidemic era.

Furtherly, we analyze the relationship between the changes of urban economy and air pollution in order to explore which cities realize green recovery and which cities are still recovering. As shown in Fig. 6, the abscissa axis presents the difference of GDP between 2020 and 2019, and the ordinate reflects the difference of PM$_{2.5}$ concentrations between 2020 and 2019. More than 150 cities are located in the fourth quadrant which indicates that these cities have achieved economic growth without worsening pollution. This paper argues that these cities have achieved green recovery, including Beijing, Shanghai, Shenzhen and most developed cities. Taking Beijing as an example, the power generation and GDP in 2020 increased by 2.5% and 2.1% than the level in 2019, which indicating that the production and economy have been back to the normal (National Bureau of Statistics, 2021a,b). Besides, the Beijing government promotes the construction of low-carbon infrastructure, implements energy-saving transformation of buildings, develops clean technology research, and takes green economic stimulus as a new economic growth point. With above measures, the proportion of secondary industry output decreased from 16.2% in 2019 to 15.8% in 2020 which contributed to the green recovery of Beijing. It also indicates that Beijing experienced a V-shaped recovery in the post-epidemic era, that is, the total output quickly turned to recovery after the recession, reaching or even exceeding the level before the epidemic (Carlsson-Szlezak et al., 2020). Cities in the second quadrants have a growth in air pollution while their economy has not returned to the pre-epidemic level. Most of these cities are located in Northeast China, such as Harbin and Shenyang. Their economy is dominated by heavy industry, so it is difficult to quickly adjust the industrial structure in the post-epidemic era. There are fourteen cities in the third quadrant, whose economy has not reached to the pre-epidemic level, and pollution has been reduced. Among them, ten cities, including Wuhan are from Hubei Province with the most serious epidemic. The economies of these cities are most affected by the epidemic and are still recovering.

3.4. Robustness check

We performed a large set of robustness checks to validate our findings. First, we tested whether there were potential effects of group-specific trends before the policy. If the AQI and the air pollutants evolved differently between the treatment group and the control group before the outbreak of COVID-19, our estimation of the effects would be false. To control for the potential effects of pre-treatment trends, we conducted the check as Bell et al. (1999) did. We kept only the samples...
up to the date before the policy and redefined the \textit{Post\_covid} dummy variable taking a value of 1 after 15th January and a value of 0 otherwise, which requires pretending that the epidemic was broken out on January 15, 2020. We chose this date because it is one week before the actual beginning of the control measures for epidemic. Apart from the implementation of the measures, these two dates have similar external environments. The coefficients of the interaction between the treatment dummy and the \textit{Post\_15Jan} dummy would be significantly different from zero during the pre-treatment period in this check. Table S6 presents the results showing that the coefficients of the interaction term were not statistically significant, which proves that there were no trends for group-specific pre-treatment.

Second, to avoid the biased estimation led by the changes of urban characteristics, we employed PSM-DID method to test the robustness of our results. The kernel matching with a quadratic kernel function is used to improve the accuracy (Huber et al., 2013). The proportion of the output value of the secondary industry, city’s GDP, fixed investment, tourism income, and export volume, are used as matching variables. There are no significant differences of urban characteristics between the treatment group and control group after matching (see Table S7).

Table S8 shows the estimation of control measures and production resumption effects using PSM-DID method. The results present that the control measures decreased PM$_{2.5}$ concentrations significantly in both lockdown cities and non-lockdown cities, the production resumption led to a significant growth of air pollution. These results are consistent with that of the DID models.

Third, the identification of assumptions in the difference-in-differences estimates is more credible when conditioned on a set of control variables. We included daily average temperature, daily relative humidity, wind direction, maximum wind speed, and a heating season dummy in Tables 1 and 2. Table S9 shows the results without control variables in regression models. After adding these control variables, our main estimations were not altered. Moreover, we also use the value and logarithm of AQI and air pollutants as the dependent variables, and the results shown in Tables 1 and 2 and Table S4 and S5 are consistent with the main results.

Fourth, to avoid the biased selection of samples, we selected different samples. We dropped four municipalities, including Beijing, Tianjin, Shanghai and Chongqing from our sample (Table S10). We also used different subsample, such as lockdown cities and non-lockdown cities, cities with higher GDP and lower GDP, etc. (Fig. 5). The results were still consistent with those from the main models.

Last, to test whether the control measures have impacts on air quality, we select different samples. We dropped four municipalities, including Beijing, Tianjin, Shanghai and Chongqing from our sample (Table S10). We also used different subsample, such as lockdown cities and non-lockdown cities, cities with higher GDP and lower GDP, etc. (Fig. 5). The results were still consistent with those from the main models.

Fig. 5. The heterogeneous effects of production resumption on the PM$_{2.5}$ concentration. Note: Blue marks represent the estimated coefficients of the effects of control measures with regression model (1), the red marks represent the estimated coefficients of the effects of production resumption with regression model (2), and the dashed black lines show 95% confidence intervals. We separate the high group from the low group for each pair of heterogeneity analyses using the mean values. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)
pollution during the production resumption period and biased our estimation, we have added the following robustness tests. We collect the information about control measures during production resumption period from local government and various media news. Some areas of 38 cities have taken temporary control measures to combat with the epidemic. We removed these 38 cities from our sample and estimated the effects of production resumption, and we also used the sample of these 38 cities for estimation. The results shown in Table S11 are consistent with that of the basic estimation, which proved that the control measures did not significantly change the estimation of the impacts of production resumption on air pollution. However, there is no denying that the control measures may affect the air pollution during the production resumption period, and our estimation of the effects of production resumption may be underestimated, which is a limitation of this study.

4. Conclusions

This paper examined whether air pollution was rebounded or kept at low level and realized green recovery in the post-COVID-19 era under the process of production resumption. Exploring the dynamic change of air quality and their influential factors in China can provide crucial information for developing epidemic recovery policies and dealing with environmental pollution issues, and shed light for other countries struggling with the epidemic. Our empirical findings have suggestive implications for policy makings.

First, this paper identified dynamic change trend of air pollution during the breakout period of COVID-19 and the post-epidemic period and quantitatively estimated the causal effects of control measure and production resumption on air pollution. Air pollution experienced a significant decline due to a series of strict control measures, and then gradually raised due to the orderly production resumption. Specifically, lockdown measures mitigated the PM$_{2.5}$ concentrations by 78.6% (44.5 μg/m$^3$), which is almost 1.7 times as that of non-lockdown cities. Production resumption increased the PM$_{2.5}$ concentrations in lockdown cities and non-lockdown cities by 43.2% (22.3 μg/m$^3$) and 35.9% (17.3 μg/m$^3$) compared with the era of COVID-19 breakout. The epidemic was more serious and the recovery was slower in lockdown cities. In general, although the economic activities of China have been gradually recovered, the pollutant level of PM$_{2.5}$ concentrations was 8.8–11.2 μg/m$^3$ lower than the level of pre-epidemic period.

Our findings indicated that the improvement of air quality only maintained in the short term. While the epidemic also brings opportunities to realize the long-term continuous decline of air pollution. Governments should seize this opportunity to strengthen the transition of clean energy and promote the development of sustainable cities. The sustainable behaviors that residents have developed during the epidemic period, such as working at home and online meetings, can be properly promoted and maintained, which will help reduce the emissions induced by commuting and business trips. In addition, governments should improve the facilities for bicycle and walking so that the residents can be encouraged to low-carbon travel and avoid the spread of the epidemic.

Second, we explored the heterogeneous impacts on air quality across cities. The effects of control measure on air pollution reduction were greater in cities with higher GDP, higher secondary industry output, more private cars and higher export volume. The outbreak of the epidemic and the control measures make the economy, production activities of these cities suffer a huge impact, and the energy consumption, especially the fuel energy consumption, drop greatly. With the process of production resumption, the PM$_{2.5}$ concentrations of these cities rebounded less.

The relative low level of air pollution may be caused by the following two reasons. On one side, some cities with heavy industry recovered more slowly, such as Fushun and Panjin in Liaoning Province, whose secondary industry output accounts for more than 50% of the total GDP (Liaoning Statistics Bureau, 2020). For the cities with abundant fuel energy resources who have not been fully recovered, governments should promote the technological revolution of the coal, accelerate the transformation of traditional coal industry to the digital, intelligent new industry, and improve the clean and efficient utilization of coal (Feng et al., 2020), so as to realize the clean and low-carbon production. Besides, governments can eliminate or transform the heavily polluting enterprises which were shut down caused by the epidemic, and carry out green technology transformation and equipment upgrading during the recovery period. On the other side, cities who promoted industrial transition and adopted green economic stimulus have started the way for green recovery, such as Beijing. For cities with developed economy, developing green building and ecological urban area, promoting low-carbon clean energy technology, improving green and low-carbon product consumption, and establishing the infrastructure of 5G would be the main measures for green and low-carbon economic recovery. These implications can also provide crucial information for developing epidemic recovery policies for other countries.

Third, although AQI and the concentrations of PM$_{2.5}$, PM$_{10}$ raised due to production resumption have not exceeded the pre-epidemic level, the concentrations of SO$_2$ and NO$_2$ showed rebound trends with the process of production resumption. Industrial sector, power sector and transportation sector are the main sectors contributed to the emission of SO$_2$ and NO$_2$ (Ro et al., 2018). During the epidemic period, 47% of the decline in PM$_{2.5}$ concentrations came from industrial sector and 32% from the transportation sector (Le Quéré et al., 2020). However, production resumption has led to the rapid recovery of the industrial, power and transportation sectors. Therefore, these sectors should be the main focus of future green recovery plan. Governments could promote the construction of renewable energy infrastructure, improve the ratio of renewable power generation, make more space for active transport, encourage telecommuting and learning.

Finally, we pointed out several directions for future research, which have not been studies in this paper due to the data or sample limitation. We only considered the impact on air pollution within 7 months after production resumption, but the epidemic has not been completely eliminated during this period, and its impact could not be ignored. Because COVID-19 may coexist with human for a long time. How to gradually return to normal life under the coexistence with the epidemic is one of the problems to be studied in the future. In addition, air quality improvements bring huge health and economy co-benefits (Ebenstein et al., 2017; Feng et al., 2021; He et al., 2016). How the air pollution change contributed by epidemic and production resumption affect health and economy co-benefits need to be identifies in future studies.

Credit author statement

Tong Feng: Methodology, Resources, Writing - original draft, Writing – review & editing.; Huibin Du: Conceptualization, Resources, Supervision.; Zhongguo Lin: Resources, writing – review & editing, Supervision.; Zhenhi Chen: writing – review & editing.; Qiang Tu: Methodology, Data.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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