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Full length article

Temporal characteristics and spatial heterogeneity of air quality changes due to the COVID-19 lockdown in China

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ARTICLE INFO

Keywords:
COVID-19 pandemic
Air quality
China
Treatment effect evaluation
Regression discontinuity

ABSTRACT

Previous studies have evaluated the impact of lockdown measures on air quality during the COVID-19 pandemic in China, but few have focused on the temporal characteristics and spatial heterogeneity of the impact across all 337 prefecture cities. In this study, we estimated the impact of the lockdown measures on air quality in each of 337 cities using the Regression Discontinuity in Time method. There was a short-term influence from January 24th to March 31st in 2020. The 337 cities could be divided into six categories showing different response and resilience patterns to the epidemic. Fine particulate matter (PM2.5) in 89.5% of the cities was sensitive to the lockdown measures. The change of air pollutants showed high spatial heterogeneity. The provinces with a greater than 20% reduction in PM2.5 and PM10 and greater than 40% reduction in NO2 during the impact period were mainly concentrated southeast of the “Hu Line”. Compared to the no-pandemic scenario, the national annual average concentration of PM2.5, NO2, PM10, SO2, and CO in 2020 were decreased by 6.3%, 10.6%, 7.4%, 9.0%, and 12.5%, respectively, while that of O3 increased by 1.1%. This result indicates that 2020 can still be used as a baseline for setting and allocating air improvement targets for the next five years.

1. Introduction

In recent years, China has achieved improvements in air quality after the establishment of a national air quality improvement target in the Five-Year Plan for Economic and Social Development (FYPESD). Different from the basis of a three-year rolling average used by the United States and other countries, China adopts the final year of the current FYPESD as the basis for setting the national air quality improvement target for the next FYPESD. The year 2020 was the final year of the 13th FYPESD, and also a unique year because of the COVID-19 outbreak. To prevent the spread of the disease, all provinces in China launched Level I responses with strictest lockdown measures to this major public health emergency in late January 2020, complying with the National Emergency Response Plan for Public Emergencies issued by the State Council. With the successful control of the epidemic, provinces gradually downgraded their response levels at different times from February to July 2020 (See Fig. S1 for details). The lockdown measures greatly reduced social and economic activities, as well as related anthropogenic emissions, thereby impacting the air quality. It is important to evaluate the changes in air quality in 2020 and justify whether that year still is a sound baseline for the 14th FYPESD.

The changes in air quality due to COVID-19 lockdown have been investigated at different in scales from worldwide, countrywide to specific cities (Adam et al., 2021; AlBayati et al., 2021; Elsaid et al., 2021; Rume and Islam, 2020). Previous studies showed that the impact of these measures on air quality was positive. Global concentrations of NO2 and fine particulate matter (PM2.5) were decreased by 5% and 4%, respectively, during the lockdown in 167 countries (Dang and Trinh, 2021). Concentrations of NO2, PM10, PM2.5, SO2, and CO generally dropped by different percentages among various international cities, while O3 concentrations increased (Benchrif et al., 2021; Kumari and Toshniwal, 2020; Liu et al., 2021; Vega et al., 2021). The focus on regional and national air quality implied similar air quality change trends in Europe, South Asia, and Southeast Asia (Belconci et al., 2021; Khan et al., 2021; Menut et al., 2020; Polednik, 2021; Roy et al., 2021). The air quality benefits resulting from the lockdown measures in response to the epidemic were reported in big cities of most countries, such as London, Delhi, and Mexico City (Mahato et al., 2020; Peralta et al., 2021; Vega et al., 2021). In addition to major urban agglomerations, the study on Hat Yai, Thailand, indicated that small cities also saw
air quality improvements during the lockdown period (Stratoulas and Nuthammachot, 2020). As a heavily polluted country, India experienced unprecedented air pollutant emission decline during the pandemic (Das et al., 2021; Sharma et al., 2020; Zhang et al., 2021).

As the first country to take measures for COVID-19 control, China had the most restrict measures and potentially largest effects on air quality. Concentrations of all pollutants went down at varying degrees at different locations (except for O3), as reported in Wuhan, Xi’an, Guangzhou, and Hangzhou (Han et al., 2021; Jiaxin et al., 2021; Shi and Brasseur, 2020; Sulaymon et al., 2021; Wen et al., 2021; Yuan et al., 2021). Megacities, provincial capital cities, and cities most severely affected by the pandemic showed a sensitive response of NO2 to lockdown, as well as for PM10 (Cai et al., 2021; Fan et al., 2020; Gao et al., 2021; Nie et al., 2021; Wang and Yang, 2021). Studies on mid-eastern China, the Dongting and Poyang Lake Region, and the North China Plain showed pollutant concentration decline during the pandemic and meteorological conditions also played an important role in air quality variation (Ding et al., 2021; Zhao et al., 2021a, 2021b). Taiwan province was different with a 3–7% increase of major pollutants because of a change of travel mode from public transportation to private cars for daily commuting (Chang et al., 2021). Different from other pollutants, O3 concentrations in the North China Plain and Yangtze River Delta were found to go up because of the enhanced atmospheric oxidation capacity (Zhu et al., 2021).

However, most previous studies focused on the influence of the COVID-19 control measures on air quality only for a single city or a given region, they do not provide detailed analysis on the variations across cities. Without such detailed analysis, the opportunity of informing future air quality improvement strategies is not fully realized. Also, most studies only focused on China’s lockdown period with the Level I response period, neglecting the possible long-term influence of lower response levels for the entirety of 2020. No study has assessed whether 2020 is still suitable as the baseline for setting pollution control targets for the 14th FYPESD.

Multiple methods were applied in previous studies, each of which has its advantages and limitations. The change of air quality during the pandemic was determined by several possible factors, including an abrupt drop in anthropogenic emissions brought by lockdown measures, a change in meteorological conditions, and annual air quality improvements because of the long-term Air Pollution Control Plan enacted. The change of social and economic activities resulted in a decline in air pollutant emissions and, therefore, impacted air quality.

As a typical quasi-experimental approach, the regression discontinuity in time (RDiT) model has lower data requirements and can support quick ex post evaluations. Through model design, it can take anthropogenic emissions declines, meteorological condition change, and air quality time trends into consideration simultaneously, therefore giving more reliable estimations of causal effects. In this study, we analyzed the temporal characteristics and the spatial heterogeneity of the impact brought by the COVID-19 lockdown on air quality in China with the RDiT model. We aimed to address several problems that previous studies have not addressed, including (1) Identifying the impact period of the pandemic on air quality; (2) Classifying the cities based on the temporal characteristics of the impact; (3) Exploring the spatial heterogeneity of the impact by evaluating each city; (4) Providing a potential baseline for air improvement targets in the 14th FYPESD. The study will help policymakers to better understand the pollution characteristics and design more accurate, scientific, and systematic air pollution control strategies.

2. Material and methods

2.1. System boundaries of the study

A conceptual study framework is illustrated in Fig. S2. The spatial boundary of this study is mainland China. National air monitoring stations are managed in 337 selected prefecture cities (See Table S1 for the list). The study was from January 1st, 2014, to December 31st, 2020. In the RDiT model, the time-series data of the air quality index (AQI), the concentration of air pollutants, and meteorological factors were used.

2.2. Econometric model

Following the research methods used in previous studies (Aufhammer and Kellogg, 2011; Davis, 2008; Li et al., 2017; Viard and Fu, 2015), the causal effect of lockdown measures on air quality was estimated with the RDiT model as follows:

\[
\ln(p_t) = \beta_0 + \beta_1 YQ_t + B \cdot \Gamma + f(\text{Date}_t) + \epsilon_t
\]

where \(p_t\) refers to the daily average concentrations of air pollutants or AQI; \(YQ_t\) is the treatment dummy of the lockdown measures; \(\Gamma\) is a vector of different variables, including time dummies, meteorological variables, and the variables in the form of interacting time dummies and meteorological variables; \(\text{Date}_t\) represents the date; \(f(\text{Date}_t)\) is a Chebyshev polynomial in time; \(\epsilon_t\) denotes the unobservable factors.

\(B\cdot\Gamma\) is used to absorb the impact of meteorological condition variation. Meteorological variables include the polynomials of daily accumulated rainfall, daily mean of wind speed, the direction of the wind, relative humidity, the maximum and minimum temperature in a day, and their lags. The time-fixed effects were controlled, including week effect, month effect, and season effect. The number of variables was expanded by interacting time dummies and meteorological variables; \(f(\text{Date}_t)\) is used to control the impact of time trends. We select the 8th Chebyshev polynomials based on the result from previous studies that the 7th, 8th, and 9th orders had a negligible effect (Aufhammer and Kellogg, 2011; Li et al., 2017). \(\epsilon_t\) is clustered at the season-of-year levels.

After controlling time trends and meteorological variables, \(\beta_1 YQ_t\) represents the impact from anthropogenic emission change brought by lockdown measures only. It is based on the assumption:

\[
E[YQ_t | \epsilon_t, YQ_t, \Gamma, f(\text{Date}_t)] = 0
\]

The assumption is reasonable because the lockdown measures were mandatory and fully implemented during the pandemic complying with the National Emergency Plan for Public Health Emergencies. The sudden change of social and economic activities resulted in a decline in air pollutant emissions and, therefore, impacted air quality.

The value of \(YQ_t\) is set by the following rule:

\[
YQ_t = \begin{cases} 1 & \text{during evaluation period} \\ 0 & \text{before and after evaluation period} \end{cases}
\]

We set six evaluation periods in 2020: January 24th to February 29th, March 1st to March 31st, April 1st to April 30th, May 1st to May 31st, June 1st to June 30th, and July 1st to July 31st. The identified period was selected as an evaluation period to assess the impact of lockdown measures on the annual air quality of China. The evaluation was carried out for each of 337 cities. The city-specific estimate, \(\hat{\beta}_1\), was obtained, which is the percentage effect of the pandemic on AQI or air pollutant concentration; \(\hat{\beta}_1\) is the causal effect of interest expressed as a percentage which is also called the treatment effect. A negative or positive value of \(\hat{\beta}_1\) indicates air quality improvement or deterioration, respectively.
Fig. 1. Treatment effect on AQI and air pollutants for the 337 cities in different evaluation periods. Blue squares represent the cities with a statistically significantly negative treatment effect of 10% level or below ($P < 0.1$, $P < 0.05$, or $P < 0.01$). Cyan dots represent the cities with insignificant treatment effects on AQI or air pollutants. Red triangles represent the cities with a statistically significantly positive treatment effect of 10% level or below ($P < 0.1$, $P < 0.05$, or $P < 0.01$). The same labels are used for Fig. 3. P1 represents January 24th to February, the same for Figs. 2, 3 and S3.
2.3. Data

The dataset of AQI and criteria air pollutants concentrations as a daily average in 337 cities for years 2014–2020 were obtained from the China National Environmental Monitoring Center (CNEMC, http://www.cnemc.cn/). The daily meteorological data were obtained from shared datasets between the China Meteorological Administration and Ministry of Ecology and Environment of China (MEE, http://www.mee.gov.cn/). The nearest meteorological station from national air quality monitoring stations in each city was chosen as the representative meteorological station. Table S2 provides summary statistics of major pollutants and meteorological variables in the 337 cities from January 1st, 2014, to December 31st, 2020.

3. Results and discussion

3.1. Temporal characteristics of the impact by lockdown measures on air quality

Fig. 1 shows the estimated treatment effects on AQI and air pollutant concentrations in different evaluation periods for the 337 cities. The proportion of cities with negative treatment effects on AQI, NO$_2$, PM$_{2.5}$, CO, and SO$_2$ were 90.5%, 97.9%, 95.8%, 89.6%, 86.9%, and 84.6%, respectively, from January 24th to February 29th. It was 86.9%, 88.1%, 83.4%, 80.7%, 81.3%, and 77.2%, respectively, in March, and abruptly dropped to 18.4%, 21.7%, 25.5%, 7.7%, 40.7%, and 39.8%, respectively, in April. Similarly, the proportion of cities with significantly negative treatment effects on AQI, NO$_2$, PM$_{10}$, PM$_{2.5}$, CO, and SO$_2$ were 80.1%, 97.9%, 85.2%, 72.7%, 71.5%, and 70.3%, respectively from January 24th to February 29th. They became 54.9%, 60.8%, 47.2%, 46.9%, 49.3%, and 48.1%, respectively, in March, and sharply dropped to 3.6%, 3.9%, 3%, 1.5%, 12.2%, and 8.6%, respectively, in April. In May, June, and July, the proportions fluctuated in a small range and were comparable with that of April. The proportion of cities with significantly positive treatment effects on AQI, NO$_2$, PM$_{10}$, PM$_{2.5}$, CO, and SO$_2$ increased in April compared with the earlier evaluation period and were relatively stable in May, June and July. The trends for O$_3$ were different, especially for January 24th to February 29th when the proportions of cities with positive and statistically significantly positive treatment effects were 89% and 67.7%, respectively.

Fig. 2 presents the average treatment effect on local air pollutant concentrations of the 337 cities. The average treatment effect on NO$_2$, PM$_{10}$, PM$_{2.5}$, CO, and SO$_2$ from January 24th to February 29th and March was negative and then became positive in April, May, June, and July, except for that of PM$_{2.5}$ and PM$_{10}$ in May whose absolute value was small. The average treatment effect on O$_3$ from January 24th to February 29th was positive and then fluctuated between negative and positive in the following periods. The kernel density estimation is shown in Fig. S3. The distribution of the treatment effects on NO$_2$, PM$_{10}$, PM$_{2.5}$, CO, and SO$_2$ was found to be centered on the left side of zero from January 24th to February 29th and March 1st to March 31st and on the right side of zero or zero in the other periods. For the treatment effects on O$_3$, the distribution was centered on the right side of zero from January 24th to February 29th and near zero in the other periods.

The results above imply that the air quality improvement resulting from the lockdown measures in China mainly occurred from January 24th to February 29th and March, with concentration declines of most pollutants, except for O$_3$. Starting in April, the concentration of most pollutants rebounded. The proportion of cities with negative or significantly negative treatment effects on AQI, NO$_2$, PM$_{10}$, PM$_{2.5}$, CO, and SO$_2$ decreased in March compared with that of January 24th to February 29th and the average treatment effect on AQI, NO$_2$, PM$_{10}$, PM$_{2.5}$, CO, and SO$_2$ in March was still negative. That indicated March was a transition period with general air quality improvement, but this benefit was less compared with that of January 24th to February 29th. The O$_3$ concentration deteriorated from January 24th to February 29th then was normal in the following periods with small fluctuations; there was no obvious transition period for O$_3$. Wang and Yang (2021) found that NO$_2$ and PM$_{10}$ fell most during the lockdown (compared to the situation before the epidemic) in nine Chinese cities most affected by the COVID-19. Our study found that NO$_2$ and PM$_{10}$ decreased 57.7% and 35.1%, respectively, from January 24th to February 29th, compared with that of the no-pandemic scenario. If there were no pandemic and other impact factors, the distribution of the treatment effect would be normally distributed and centered on zero. But, the distribution of treatment effect of most pollutants centered on the right side of zero in April and following periods (See Fig. S3) indicates a compensatory effect. The industries and transportation sector recovered and produced more products or transported more goods to compensate for the suspension during the lockdown, thereby leading to a deterioration in air quality.

China was the first major economy to recover after a slowdown induced by the pandemic (Wang and Zhang, 2021) and became the only country that achieved positive economic growth in 2020 (among major economies). During the pandemic, China made great efforts to simultaneously seek control of COVID-19 spread and sustain economic recovery. The rate of enterprises that returned to operate (RERO) for enterprises above the designated size and the rate of employees who returned to work (RERW) had already reached 83.1% and 51.9%, respectively, by February 23rd, 2020. But the RERO for middle
small-sized enterprises was only 30%. The RERO and RERW for enterprises above the designated size reached 98.6% and 89.9%, respectively, at the end of March, and 99% and 94%, respectively, on April 14th, 2020 (Committee, 2021a, 2021b). Four key indicators of social and economic activities, including the sequential growth rate of GDP, the year-on-year growth rate of industrial added value, power generation, and highway freight turnover, showed negative growth in the first quarter but rebounded to positive growth from April to December (Fig. S4).

The evidence above demonstrates that most social and economic activities in China started to recover in March 2020. The improvement brought by lockdown measures on air quality was a short-term influence from late January to March (with March as a transition). The variation of treatment effect on air pollutants matches with that of RERO, RERW, and other main socio-economic indicators, except for O$_3$. The weakened titration of ozone by NO due to reduced NO concentration, as well as the enhanced atmospheric oxidation capacity associated with the meteorological conditions during the lockdown, were believed to be the major reasons for O$_3$ increase (Shi and Brasseur, 2020; Zhu et al., 2021). As Fig. S1 shows, most provinces downgraded from Level I to lower response levels at the end of February, but air quality improvement continued through March. If we equate lockdown to the Level I response, we are likely to underestimate the impact of the pandemic on air quality. The estimated results from April to July imply that Level III or Level IV responses did not bring improvements in air quality.

3.2. City classification based on temporal variation of treatment effects

To explore the characteristics of treatment effect temporal variation, the 337 cities are classified into six types based on the PM$_{2.5}$ negative or positive effects from January 24th to February, March, and April.
(Fig. 3). Type I cities are defined as cities in which PM$_{2.5}$ improved in all 3 periods, but in April the number of cities with statistically significant negative treatment effects decreased. Type II cities are defined as cities in which the concentration of PM$_{2.5}$ decreased in the first period but rebounded in March and April. Type III cities are defined as cities in which the concentration of PM$_{2.5}$ increased in all periods in February but dropped in March. PM$_{2.5}$ did not improve in all periods in Type VI cities (which account for 4.5% of the 337 cities). The number of Type I to Type VI is 21, 231, 50, 15, and 15, respectively. Different city types reflect different response patterns of PM$_{2.5}$ to lockdown measures and also show varied resiliences to the pandemic. PM$_{2.5}$ in 89.5% of cities, including Type I, II, and III, was highly sensitive to the lockdown measures. The remaining cities, in which PM$_{2.5}$ had a lag improvement or no improvement, are mainly located in the northeast or western regions of China that are relatively remote, less industrialized, and less

![Box diagram of treatment effects for various pollutants in the 337 cities (beginning with the Level I response to end of March, 2020).](image)

Table 1

| Region (337 cities) | Statistical indicator | PM$_{2.5}$ | SO$_2$ | NO$_2$ | CO | O$_3$ | PM$_{10}$ | AQI |
|---------------------|-----------------------|------------|--------|--------|----|-------|-----------|------|
| Nation (337 cities) | Mean                  | -0.208     | -0.231 | -0.418 | -0.153 | 0.074 | -0.268 | -0.215 |
|                     | Standard deviation    | 0.159      | 0.225  | 0.158  | 0.148  | 0.101 | 0.154 | 0.14  |
|                     | Min                   | -0.595     | -0.848 | -1.055 | -0.495 | -0.343 | -0.676 | -0.551 |
|                     | Max                   | 0.326      | 0.486  | 0.03   | 1.129  | 0.416  | 0.303  | 0.266 |
| BTH (2-26 cities)   | Mean                  | -0.261     | -0.341 | -0.405 | -0.248 | 0.142 | -0.346 | -0.344 |
|                     | Standard deviation    | 0.076      | 0.138  | 0.08   | 0.119  | 0.12  | 0.105 | 0.093 |
|                     | Min                   | -0.471     | -0.67  | -0.534 | -0.45   | -0.087 | -0.511 | -0.483 |
|                     | Max                   | -0.133     | -0.173 | -0.23  | 0.161  | 0.397 | -0.083 | -0.137 |
| Yangtze River Delta (41 cities) | Mean | -0.294 | -0.143 | -0.454 | -0.199 | 0.086 | -0.331 | -0.316 |
|                     | Standard deviation    | 0.169      | 0.144  | 0.145  | 0.11   | 0.075 | 0.118 | 0.063 |
|                     | Min                   | -0.527     | -0.51  | -0.945 | -0.495 | -0.088 | -0.576 | -0.477 |
|                     | Max                   | -0.007     | 0.242  | -0.155 | 0.101  | 0.247 | -0.028 | -0.181 |
| Fenwei plain (11 cities) | Mean | -0.138 | -0.3 | -0.378 | -0.156 | 0.103 | -0.266 | -0.214 |
|                     | Standard deviation    | 0.066      | 0.158  | 0.086  | 0.093  | 0.081 | 0.094 | 0.08 |
|                     | Min                   | -0.23      | -0.552 | -0.54  | -0.351 | -0.038 | -0.458 | -0.238 |
|                     | Max                   | -0.04      | -0.057 | -0.269 | -0.008 | 0.234 | -0.147 | -0.068 |
| The border of JSHA (15 cities) | Mean | -0.289 | -0.301 | -0.425 | -0.184 | 0.055 | -0.336 | -0.315 |
|                     | Standard deviation    | 0.081      | 0.095  | 0.1    | 0.124  | 0.058 | 0.069 | 0.057 |
|                     | Min                   | -0.439     | -0.506 | -0.658 | -0.394 | -0.029 | -0.404 | -0.398 |
|                     | Max                   | -0.092     | -0.177 | -0.238 | 0.007  | 0.171 | 0.194 | 0.194 |
| Pearl River Delta (9 cities) | Mean | -0.301 | -0.157 | -0.505 | -0.189 | 0.059 | -0.383 | -0.313 |
|                     | Standard deviation    | 0.082      | 0.142  | 0.104  | 0.085  | 0.086 | 0.11  | 0.072 |
|                     | Min                   | -0.453     | -0.388 | -0.639 | -0.359 | -0.109 | -0.494 | -0.385 |
|                     | Max                   | -0.179     | 0.038  | -0.295 | -0.11  | 0.162 | 0.153 | -0.191 |
| Cheng-Yu area (16 cities) | Mean | -0.185 | -0.142 | -0.464 | -0.197 | 0.1    | -0.245 | -0.228 |
|                     | Standard deviation    | 0.095      | 0.253  | 0.09   | 0.081  | 0.086 | 0.081 | 0.072 |
|                     | Min                   | -0.312     | -0.588 | -0.655 | -0.346 | -0.057 | -0.345 | -0.355 |
|                     | Max                   | 0.014      | 0.486  | -0.318 | -0.048 | 0.232 | -0.111 | -0.109 |
compared to a situation without the COVID-19 pandemic, as a result of measures on air quality. The treatment effect of the 337 cities was an important period for the evaluation of the impact of the lockdown impact, we concluded that January 24th to March was the most significant reduction of transportation activities. By contrast, the concentration of O₃ increased by 7.4% during the same period, and increased in 266 out of the 337 cities.

The spatial heterogeneity of treatment effect is discussed among six air pollution control key regions (APCKRs), i.e., areas of poor air quality in China (Table 1). In terms of PM$_{2.5}$, the Pearl River Delta and Yangtze River Delta experienced the largest decline compared to the no-pandemic scenario, of 30.1% and 29.4%, respectively, while the Fenwei plain had the smallest decline by 13.8%. In terms of SO$_2$, the Beijing-Tianjin-Hebei (BTH) area and the border area of Jiangsu-Shandong-Henan-Anhui (JSHA) experienced the largest decrease of 34.1% and 30.1%, respectively, while the Cheng-Yu area had the smallest decrease of 14.2%. For NO$_2$, the Pearl River Delta and Cheng-Yu areas experienced the largest declines, of 50.5% and 46.4%, respectively, and the Fenwei plain had the smallest decrease with 37.8%; For O$_3$, BTH area and Fenwei plain had the largest increase of 14.2% and 10.3%, respectively, and the smallest increase of 5.5% occurred in the JSHA area.

When the average treatment effect of each pollutant was aggregated to the province level, as shown in Fig. 5, it is apparent that the large treatment effect of PM$_{2.5}$, PM$_{10}$ and NO$_2$ are concentrated in the southeast of China as marked by the red dotted line in Fig. 5(a–c)—called the "Heihe-Tengchong Line", or the "Hu Line." The southeast area of the line occupies about 43% of the total land area of the country, with 94% of the total population and contributing 95.7% of the national GDP. As shown in Fig. 5(a–c), the provinces with PM$_{2.5}$ and PM$_{10}$ declines of greater than 20%, and a NO$_2$ decline greater than 40%, are mainly concentrated southeast of the "Hu Line," indicating that the control measures had a greater impact on air quality in the areas with a higher level of social and economic activities. According to the RDiT model design in this study, the treatment effect reflected the impact of the emission change brought by the pandemic. That meant the emission declines to the southeast of the “Hu Line” were greater.

### 3.4. The impact on the annual average concentration of pollutants at national, regional, and provincial levels

In China, air quality management, including air quality improvement planning, target allocation, and performance evaluation, is based on the annual average concentrations of pollutants. This study estimated the annual average concentration of all pollutants for each of the 337 cities, each province, each APCKR, and the whole country, under a no-pandemic scenario. The results for 31 provinces and 6 APCKRs are shown in Table S3 and Table S4, respectively. Compared to the no-pandemic scenario, the national annual average concentrations of PM$_{2.5}$, NO$_2$, PM$_{10}$, SO$_2$, and CO decreased by 6.3%, 10.6%, 7.4%, 9.0%, respectively.
and 12.5%, respectively, while that of O3 increased by 1.1% (Table 2). Adding the changes to the actually values, it is found that the national annual average concentrations of PM2.5, O3, NO2, PM10, SO2, and CO were 34.9, 88.4, 27.3, 60.8, 11.1 μg/m³ and 0.8 mg/m³, respectively, if there was no pandemic. This result can provide a potential baseline for setting a national air improvements target for the 14th FYPESD. The regional and provincial annual average concentration of pollutants under a no-pandemic scenario could be helpful for policymakers when they allocate the national target to the regional and provincial levels.

4. Conclusion and policy implications

The COVID-19 pandemic and associated control measures reduced socio-economic activities, and improved air quality across China. Our study used the RDIT model to quantify the impact of the pandemic on air quality for 337 cities. The impact of the lockdown measures on air quality is in the short-term from late January to the end of March, although varying levels of response measures were implemented under a no-pandemic scenario. This result can provide a potential baseline for air quality control problems into the future.

In the 14th FYPESD, the collaborative control of PM2.5 and O3 pollution should be emphasized. But the increased concentration of O3 during the epidemic, especially in the BTH region, provides a warning that we need to fully understand the complexities and O3 control. During the epidemic, there were few coordinated emission reductions of O3. To achieve the coordinated control of PM2.5 and O3 pollution during the 14th FYPESD, different emission reduction paths need to be taken, and targeted emission reduction strategies need to be formulated, to address pollution control problems into the future.

CRediT authorship contribution statement

Jinghai Zeng: Conceptualization, Methodology, Software, Visualization, Resources, Writing – original draft. Can Wang: Supervision, Writing – review & editing.

Declaration of Competing Interest

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

Acknowledgments

This research was funded by the Key Technologies Research and Development Program (2017YFA0603602) and the National Natural Science Foundation of China (71773062).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2022.106223.

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In the 14th FYPESD, the collaborative control of PM2.5 and O3 pollution should be emphasized. But the increased concentration of O3 during the epidemic, especially in the BTH region, provides a warning that we need to fully understand the complexities and O3 control. During the epidemic, there were few coordinated emission reductions of O3. To achieve the coordinated control of PM2.5 and O3 pollution during the 14th FYPESD, different emission reduction paths need to be taken, and targeted emission reduction strategies need to be formulated, to address pollution control problems into the future.

CRediT authorship contribution statement

Jinghai Zeng: Conceptualization, Methodology, Software, Visualization, Resources, Writing – original draft. Can Wang: Supervision, Writing – review & editing.

Declaration of Competing Interest

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

Acknowledgments

This research was funded by the Key Technologies Research and Development Program (2017YFA0603602) and the National Natural Science Foundation of China (71773062).

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.resconrec.2022.106223.

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